UNIVERSITY OF Hull

FACULTY OF SCIENCE and ENGINEERING

The plagiarism declaration below must be read and understood.
Attaching this cover sheet to work is taken to be the equivalent of submitting a signed copy of the form.
Please read the declaration carefully and query with your department if you do not understand its meaning.

STUDENT SUBMISSION AND FEEDBACK FORM

*Stick **barcode** here if **hard copy submission** – no need for barcode for electronic submission*

STUDENT NUMBER	201304130		
Degree Programme	MSc Artificial Intelligence and Data Science	Year of Study	1
Module Code	771763	Date	7th April 2022
Module Title	Understanding Artificial Intelligence		
Assignment Title	Portfolio of Work		
Word Count	780	Tutor setting assessment	Dr Nina Dethlefs

Plagiarism Declaration
I declare that the work that I am submitting for assessment contains no section copied in whole or in part from any other source unless it is explicitly identified by means of quotation marks. I declare that I have also acknowledged such quotations by providing detailed references in an approved format. I understand that either or both unidentified and unreferenced copying constitute plagiarism, which is one of a number of very serious offences under the University's Code of Practice on the Use of Unfair Means.
(Information on the Code of Practice is available from the online student handbook – www.hull.ac.uk/handbook)

Assessment Criteria	Markers Feedback	Mark(s)
		/100
	Agreed Internal Provisional Mark	

PLEASE NOTE THAT THIS MARK IS PROVISIONAL AND IS SUBJECT TO VERIFICATION BY THE EXTERNAL EXAMINER AND THE MODULE BOARD OF EXAMINERS

COMPONENT 1

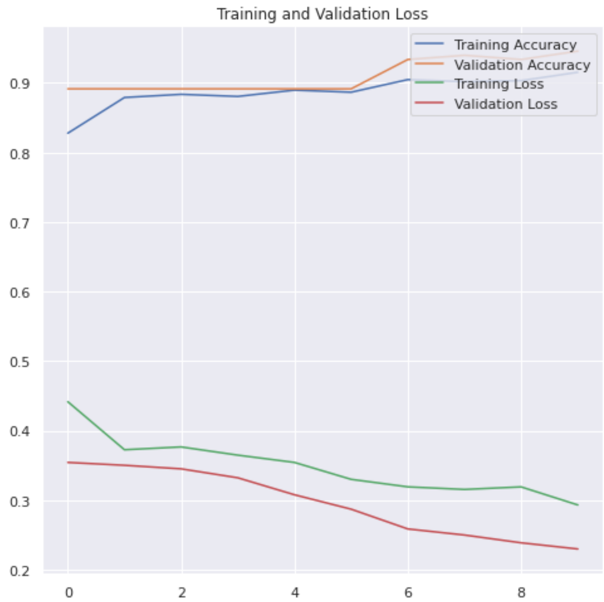
Q.1 **Specify the accuracy you achieved across 3 architectural modifications (e.g., different number of layers, different hyperparameters, etc**

Number of Layers	Activation Function	Optimization Algorithm	Number of Iterations (epoch)	Loss Function	Accuracy %	Test Accuracy %	Test Loss	Time
3	Relu	Adam	10	Categorical cross-entropy	88.3	89.1	nan	CPU times: user 3.64 s, sys: 151 ms, total: 3.79s Wall time: 5.36s
3	Relu	Adam	10	Binary cross-entropy	85.6	89.1	1.6726	CPU times: user 2.47 s, sys: 107 ms, total: 2.58s Wall time: 2.39s
3	Relu	ADAdelta	10	Binary cross-entropy	82.7	89.1	1.5859	CPU times: user 2.47 s, sys: 125 ms, total: 2.6 s Wall time: 3 s
3	Sigmoid	RMSprop	10	Binary cross-entropy	91.5	93.9	0.2154	CPU times: user 1.68 s, sys: 70.1 ms, total: 1.75s Wall time: 2.68s
3	Sigmoid	Adam	10	Binary cross-entropy	91.5	94.5	0.2302	CPU times: user 2.45 s, sys: 103 ms, total: 2.55s Wall time: 3.51s
3	Tanh	SGD	10	Binary cross-entropy	84.7	89.7	0.8909	CPU times: user 2.21 s, sys: 107 ms, total: 2.32s Wall time: 2.15s
4	Sigmoid	RMSprop	10	Binary cross-entropy	88.3	89.1	0.3480	CPU times: user 3.01 s, sys: 110 ms, total: 3.12s Wall time: 3.01s
5	Relu	RMSprop	20	Binary cross-entropy	86.4	89.7	1.6726	CPU times: user 6.69 s, sys: 225 ms, total: 6.92s Wall time: 10.4s
5	Sigmoid	RMSprop	10	Binary cross-entropy	88.3	89.1	0.3472	CPU times: user 2.75 s, sys: 121 ms, total: 2.88s Wall time: 2.64s
6	Relu	Adam	10	Binary cross-entropy	89.1	92.1	0.2537	CPU times: user 3.91 s, sys: 174 ms, total: 4.08s Wall time: 7 s

6	Relu	RMSprop	10	Binary cross-entropy	84.8	89.7	0.3900	CPU times: user 4.14 s, sys: 142 ms, total: 4.28s Wall time: 8.37s
7	Relu	Adam	10	Binary cross-entropy	88.8	89.7	0.3077	CPU times: user 4.12 s, sys: 200 ms, total: 4.32s Wall time: 6.05s
7	Tanh	Adam	5	Binary cross-entropy	87.6	92.1	0.9406	CPU times: user 2.9 s, sys: 118 ms, total: 3.02 s Wall time: 3.98s

Binary cross-entropy was used as the Loss function for the network model, as the Test Loss output when categorical cross-entropy was used nan or 0. There isn't much difference between Test and Train accuracies, therefore, the model was not overfitting with the hyperparameters used.

Layers: 3
Activation Function: Sigmoid
Optimizer: Adam
Loss Function: Binary cross-entropy
Accuracy %: 91.5
Val Accuracy %: 94.5
Test Loss: 0.2302



Q.2 **Why do you think your accuracy is not higher/lower?**

The accuracy increased when the following was applied:

- When the Loss function was categorical cross-entropy, Test Loss was nan or 0 and accuracy was lower. The Loss function was changed to Binary cross-entropy and the accuracy increased.
- Other activation functions were tested, however, Sigmoid successfully applied with the binary loss function[1], was the suitable choice as the threshold takes a value between 0 and 1.[2]
- The optimizer Adam outputted the better accuracy.

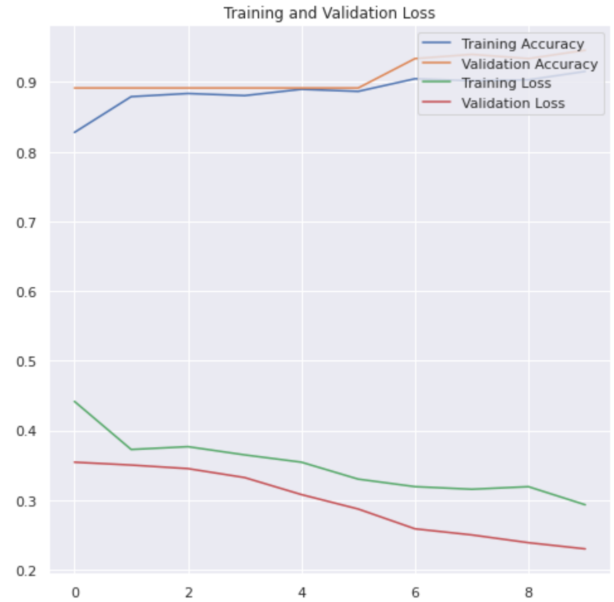
Q.3 **What effect does the optimisation function have on network performance?**

Four different optimizers were tested on the neural network. The optimizers that provided the best accuracy were Adam and RMSprop depending on the other components (layers, loss function). The optimiser that scored the highest accuracy was Adam. ADAdelta and SGD scored the lowest accuracies. Therefore, the optimizer affects the network performance as seen:

---

1 Nwankpa, C. E., Ijomah, W., Gachagan, A. and Marshall, S., (2018). Activation Functions: Comparison of Trends in Practice and Research for Deep Learning [online]. [Viewed 7 April 2022]. Available from: https://arxiv.org/abs/1811.03378

2 The Most Used Activation Functions: Classic Versus Current [online]. (2020). IEEE Xplore. [Viewed 7 April 2022]. Available from: https://ieeexplore.ieee.org/abstract/document/9108942



Performance using Adam as the optimizer

Layers: 3
ActivationFunction: Sigmoid
Accuracy %: 91.5
Val Accuracy %: 94.5
Test Loss: 0.2302

Performance using ADAdelta as the optimizer

Layers: 3
ActivationFunction: Relu
Accuracy %: 82.7
Val Accuracy %: 89.1
Test Loss: 1.5859

Q.4 **What happens if you include more than 4 layers?**

There are varied effects when the layers are increased. The layers were increased using optimizers Adam and RMSprop.

- Sigmoid: Increasing the layer above 3 using Adam and RMSprop as the optimiser, reduced accuracy from 94.5% to 89.1% and increased the test loss from 0.2302 to 0.5558(Adam) and 0.2302 to 0. 3480 (RMSprop) and increased CPU time spent than a lower number of layers.
- Relu: Increasing the layers to 6, using Adam, increased accuracy from 89.1% to 92.1% than lower no of layers, reduced test loss from 1.6726 to 0.2537 and more time spent.
- Tanh: Increasing the layers, using Adam and in with only 5 epochs had an increase in accuracy from 89.7% to 92.1%), the test loss increased from 0.8909 for 3 layers to 0.9406 for 7 layers.

Q.5 **What is the effect of the data size on your accuracy?**

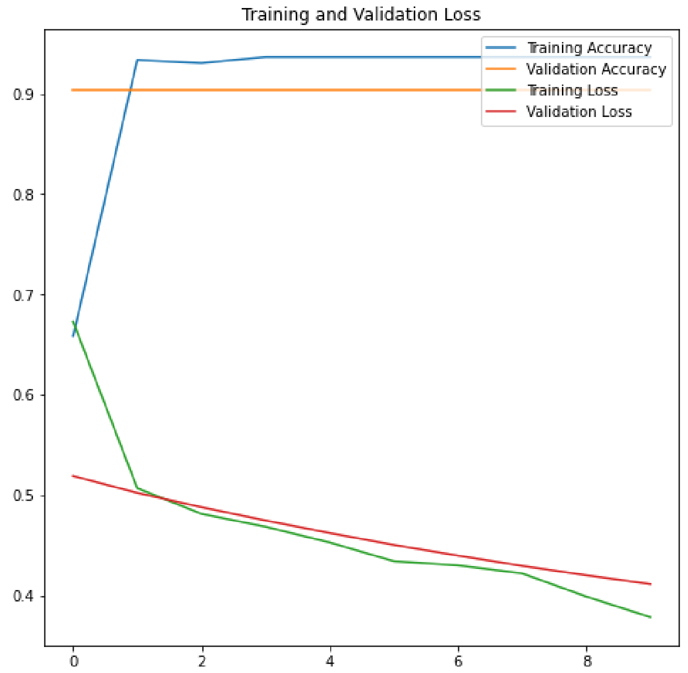
- Changing the size of the data to half of it (:414) with the following parameters:

Number ofLayers	**Activation Function**	**Optimization Algorithm**	**Number of Iterations (epoch)**	**Loss Function**	**Accuracy %**	**Test Accuracy %**	**Test Loss**	**Time**
3	Sigmoid	Adam	10	Binary cross-entropy	93.6	90.3	0.3175	CPU times: user 1.66 s, sys: 100 ms, total: 1.76s Wall time: 2.97 s

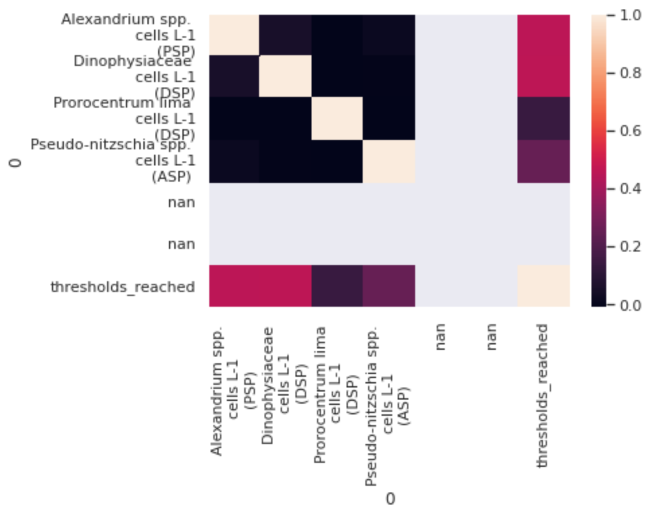
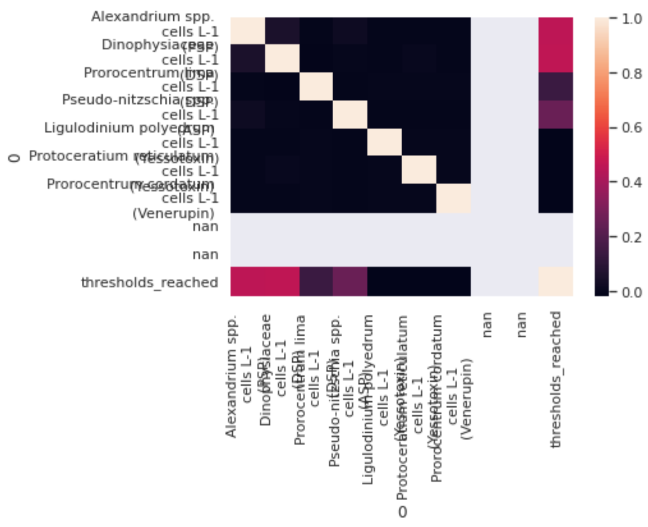
This can be compared to the results provided in the table above when the data was (:828):

3	Sigmoid	Adam	10	Binary cross-entropy	91.5	94.5	0.2302	CPU times: user 2.45 s, sys: 103 ms, total: 2.55s Wall time: 3.51s

As can be seen, the Test accuracy decreased, the Test loss increased while the training Accuracy increased when I halved the trained data size from 828 to 414. The Test accuracy score stayed the same all through the training: 90.3 - when the data size was halved – Table below:

Original data size (828) used:	**Half data size (414):**
	

- The heatmap below shows that all the variables correlate with each other. There are also some correlations between the output variable "thresholds_reached" and the individual inputs tested.

	
	After adding more columns from the Dataframe.

Bibliography

Team, K., 2022. *Keras documentation: Conv2D layer*. [online] Keras.io. Available at: <https://keras.io/api/layers/convolution_layers/convolution2d/> [Accessed 7 April 2022].

Nwankpa, C. E., Ijomah, W., Gachagan, A. and Marshall, S., (2018). *Activation Functions: Comparison of Trends in Practice and Research for Deep Learning* [online]. [Viewed 7 April 2022]. Available from: https://arxiv.org/abs/1811.03378

The Most Used Activation Functions: Classic Versus Current [online]. (2020). *IEEE Xplore*. [Viewed 7 April 2022]. Available from: https://ieeexplore.ieee.org/abstract/document/9108942

Medium. 2022. *Activation Functions with Derivative and Python code: Sigmoid vs Tanh Vs Relu*. [online] Available at: <https://medium.com/@omkar.nallagoni/activation-functions-with-derivative-and-python-code-sigmoid-vs-tanh-vs-relu-44d23915c1f4> [Accessed 7 April 2022].

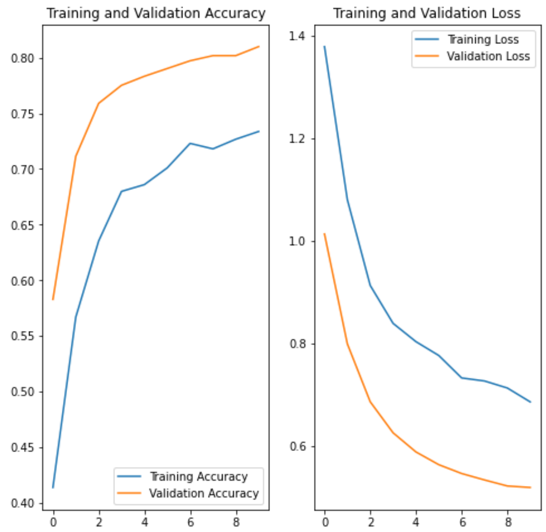
COMPONENT 2

Q.1 How long does the network need to train until reaching an accuracy of 95% (or does it not reach this level at all)?

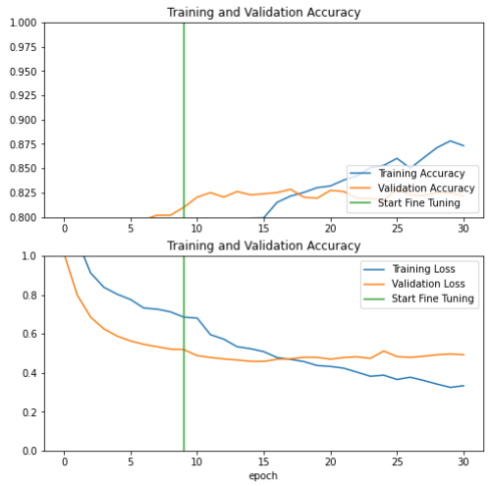
- The maximum accuracy achieved after fine-tunning the model was 90.5% with CPU times total: 1.86 s. Wall time: 5.43s.

First training:

After Data Augmentation:



After Fine-tune process:



Q.2 What is the trade-off between using many layers (I.e., having a "deeper" network) and accuracy? And layers and time?

- With 5 layers and using Max pooling, the accuracy slightly decreased from 90.5% to 90.2% with CPU times increased to total: 1.98 s. Wall time decreased to: 2.95s.

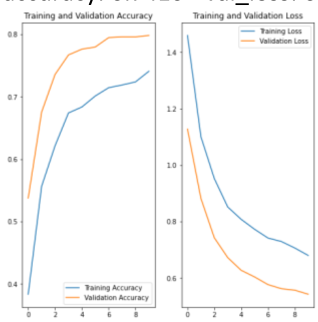
Q.3 What is the effect of changing the pooling mechanism, e.g., average vs max? Add graphs of average vs max pooling.

- The accuracy slightly increased when the pooling mechanism was changed from Average pooling to Max pooling. The final model training outputted 82.1% for Average pooling and 82.2% for max pooling:

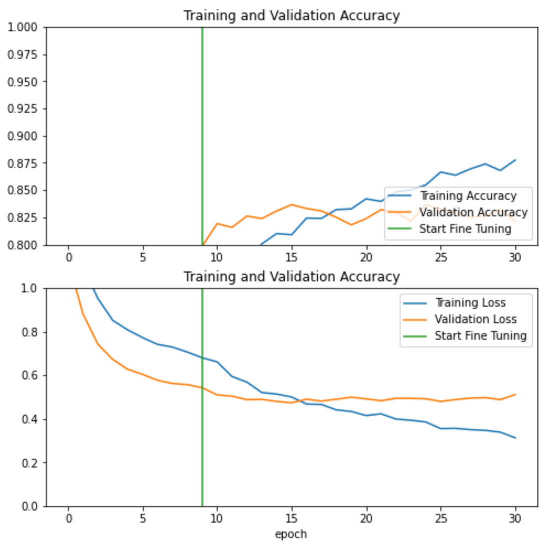
Average pooling

First training:
accuracy: 0.8475 - val_loss: 1.2212 - val_accuracy: 0.6072
CPU times: user 35.1 s, sys: 2.54 s, total: 37.6 s
Wall time: 53.2 s

Second training – Augmentation:
accuracy: 0.7410 - val_loss: 0.5426 - val_accuracy: 0.7984



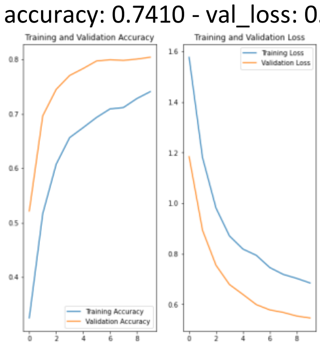
Third training – Fine-tuned model:
accuracy: 0.8776 - val_loss: 0.5110 - val_accuracy: 0.8216
CPU times: user 1min 54s, sys: 5.87 s, total: 1min 59s
Wall time: 3min 44s



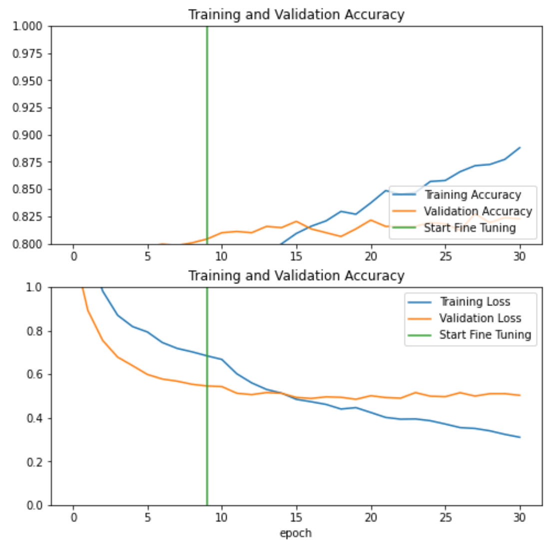
Max pooling

First training:
accuracy: 0.9635 - val_loss: 1.8782 - val_accuracy: 0.5817
CPU times: user 37.1 s, sys: 2.4 s, total: 39.5 s
Wall time: 53.1 s

Second training – Augmentation:
accuracy: 0.7410 - val_loss: 0.5461 - val_accuracy: 0.8042



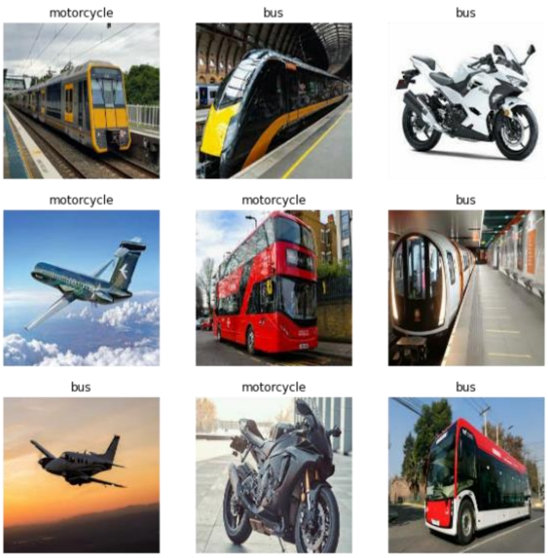
Third training – Fine-tuned model:
accuracy: 0.8880 - val_loss: 0.5032 - val_accuracy: 0.8227
CPU times: user 1min 55s, sys: 6.4 s, total: 2min 1s
Wall time: 3min 29s



20 images collected and used to test the network model:

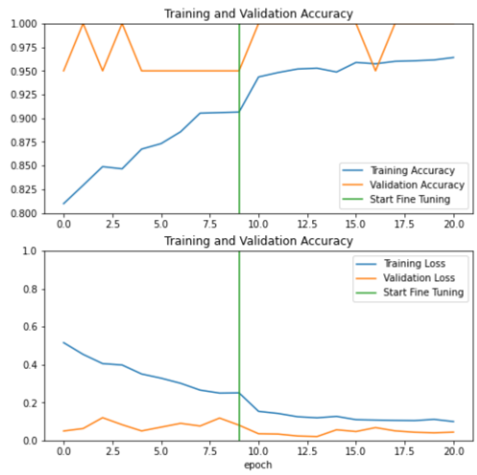
How well does your network do at classifying these images?

- The model didn't accurately identify all the images, however, it only identified one bus correctly.



Does fine-tuning make a difference?

- Fine tuning increased the accuracy but did not make any difference to how the network classified the images.



After Augmentation

After Fine-tune

Bibliography

Team, K., 2022. *Keras documentation: Conv2D layer*. [online] Keras.io. Available at: <https://keras.io/api/layers/convolution_layers/convolution2d/> [Accessed 7 April 2022].

TensorFlow. 2022. *Convolutional Neural Network (CNN) | TensorFlow Core*. [online] Available at: <https://www.tensorflow.org/tutorials/images/cnn> [Accessed 7 April 2022].

TensorFlow. 2022. *Image classification | TensorFlow Core*. [online] Available at: <https://www.tensorflow.org/tutorials/images/classification> [Accessed 7 April 2022].

COMPONENT 3

Energy and Policy Considerations for Deep Learning in NLP

Training a deep network can cost a lot. In this paper, the researchers quantify the financial and ecological costs (carbon footprint) associated with training deep networks to obtain highly accurate results within NLP tasks.[1] Furthermore, it raises concerns about the disparity in computational resources between academia and industry. [2] The researchers use NLP models to illustrate the case and support their arguments.[3] The issues discussed in the paper also apply to the computer vision community.[4]

The researchers conducted an analysis of the energy required to train several popular common NLP models and the total sum of resources - including tuning and experiments. They found that the process of training models can emit more than 626,155 pounds of CO2e (carbon dioxide) and can cost upwards of $3,201,722.[5]

In the paper, the researchers analysed and trained four models to measure their energy usage: the Transformer model, ELMO, BERT, and GPT-2.[6] Each of the models was reportedly trained for one day on a single NVIDIA Titan X GPU, except the ELMO model which was trained on 3 NVIDIA GTX 1010 Ti GPUs. During the training, the researchers captured the hardware that the models were trained on and measured the power consumption of the training hardware, the duration of the training, and the CO2 emissions as a result, as well as the costs associated with the training.[7]

In the paper, the researchers referred to prior research reports which show that computationally-intensive such as the Transformer base model and big mode, the ELMO model, the BERT model, and the GPT-2 large model, achieve great results.[8] However, achieving those results require hours, days and even weeks of training, experimenting with different architectures and quantities of parameters which can increase the costs of training by the thousands.[9] The researchers found that TPUs were more cost-efficient than GPUs such as the BERT model.[10] Fine-tuning a model via repetitive searches of model architectures and hyperparameters vastly increases the financial and energy costs.[11] The researchers found that training a model such as BERT is somewhat the same as the environmental cost of a trans-American flight[12] and the costs of training the models can range from $41 to $43,008. These excessive costs can make it unattainable for those without access to significant resources.[13]

To encourage researchers to be more careful when dealing with the issues detailed above, the researchers proposed the following could help resolve these ethical issues[14]:

---

[1] Taha, A., (2021). Energy and Policy Considerations for Deep Learning in NLP [online]. *Medium*. [Viewed 3 April 2022]. Available from: https://ahmdtaha.medium.com/energy-and-policy-considerations-for-deep-learning-in-nlp-ce490ffdc209
[2] Taha, A., (2021). Energy and Policy Considerations for Deep Learning in NLP [online]. *Medium*. [Viewed 3 April 2022]. Available from: https://ahmdtaha.medium.com/energy-and-policy-considerations-for-deep-learning-in-nlp-ce490ffdc209
[3] Taha, A., (2021). Energy and Policy Considerations for Deep Learning in NLP [online]. *Medium*. [Viewed 3 April 2022]. Available from: https://ahmdtaha.medium.com/energy-and-policy-considerations-for-deep-learning-in-nlp-ce490ffdc209
[4] Taha, A., (2021). Energy and Policy Considerations for Deep Learning in NLP [online]. *Medium*. [Viewed 3 April 2022]. Available from: https://ahmdtaha.medium.com/energy-and-policy-considerations-for-deep-learning-in-nlp-ce490ffdc209
[5] Strubell, E., Ganesh, A. and McCallum, A., 2019. *Energy and Policy Considerations for Deep Learning in NLP*. [online] arXiv.org. Available at: <https://arxiv.org/abs/1906.02243> [Accessed 7 April 2022].
[6] Strubell, E., Ganesh, A. and McCallum, A., 2019. *Energy and Policy Considerations for Deep Learning in NLP*. [online] arXiv.org. Available at: <https://arxiv.org/abs/1906.02243> [Accessed 7 April 2022].
[7] Montreal AI Ethics Institute. 2021. *Energy and Policy Considerations in Deep Learning for NLP | Montreal AI Ethics Institute*. [online] Available at: <https://montrealethics.ai/energy-and-policy-considerations-in-deep-learning-for-nlp/> [Accessed 7 April 2022].
[8] Montreal AI Ethics Institute. 2021. *Energy and Policy Considerations in Deep Learning for NLP | Montreal AI Ethics Institute*. [online] Available at: <https://montrealethics.ai/energy-and-policy-considerations-in-deep-learning-for-nlp/> [Accessed 7 April 2022].
[9] Strubell, E., Ganesh, A. and McCallum, A., 2019. *Energy and Policy Considerations for Deep Learning in NLP*. [online] arXiv.org. Available at: <https://arxiv.org/abs/1906.02243> [Accessed 7 April 2022].
10 Strubell, E., Ganesh, A. and McCallum, A., 2019. Energy and Policy Considerations for Deep Learning in NLP. [online] arXiv.org. Available at: <https://arxiv.org/abs/1906.02243> [Accessed 7 April 2022].
[11] [11] Montreal AI Ethics Institute. 2021. *Energy and Policy Considerations in Deep Learning for NLP | Montreal AI Ethics Institute*. [online] Available at: <https://montrealethics.ai/energy-and-policy-considerations-in-deep-learning-for-nlp/> [Accessed 7 April 2022].
[12] Eyerys. *Training AI Model Uses As Much Carbon As Five Cars In Their Lifetimes, Researchers Said*. [online] Available at: <https://www.eyerys.com/articles/timeline/training-ai-model-uses-much-carbon-five-cars-their-lifetimes-researchers-said#event-a-href-articles-timeline-britney-spears-unfollows-sister-on-instagrambritney-spears-starts-2022-by-unfollowing-her-sister-on-instagram-a> [Accessed 6 January 2022].
[13] Montreal AI Ethics Institute. 2021. *Energy and Policy Considerations in Deep Learning for NLP | Montreal AI Ethics Institute*. [online] Available at: <https://montrealethics.ai/energy-and-policy-considerations-in-deep-learning-for-nlp/> [Accessed 7 April 2022].
14 Strubell, E., Ganesh, A. and McCallum, A., 2019. Energy and Policy Considerations for Deep Learning in NLP. [online] arXiv.org. Available at: <https://arxiv.org/abs/1906.02243> [Accessed 7 April 2022].

- Authors are advised to report model training time and hyperparameters sensitivity as this will enable comparison across different models, which will then allow future consumers of such models to evaluate accurately whether the needed computational resources are compatible with their setting.[15]
- Academic researchers are recommended to collect recourses to build a shared compute/data centres at the level of funding agencies such as the US National Science Foundation, as this would provide equitable access to computational resources for all researchers.[16]
- It is proposed that the AI industry and academia should try to promote more computationally efficient algorithms as this could have a notable impact on the cost of developing and tuning in natural language processing NLP.[17]

This work sparked a debate in the field of natural language processing (NLP) about carbon production and the AI research community's reliance on accuracy for assessing the worthiness of results.[18] Carbon-efficient workshops at a number of top-tier NLP conferences are an example of the attempts to raise awareness of these issues.[19] As AI researchers and engineers work to develop more eco-responsible AI systems, there is hope that awareness of these issues will continue to gain traction.[20] Additional research is still needed, particularly to make devices that can be compatible with current deep learning structures.[21] Making reporting a standard research approach will also help.[22]

Other areas of Applied AI where there may be a similar ethical challenge.
The use of energy creates CO2 and according to Gerry McGovern (author of the book World Wide Waste), given that AI utilises intense amounts of energy, the more the demand for AI systems, the more power is used.[23] Over the past decade, data centres have become more efficient with electricity usage, however, according to McGovern, many experts have considered that electricity accounts only for roughly 10% of the centres' CO2 emissions, which means that in total data centres' produce a lot of CO2 emissions.[24]

Businesses' environmental impact: In order to reduce energy consumption, businesses that are concerned about their ecological footprint should produce more high-quality data instead of creating high-quality data.[25] Unused data should be deleted after a period of time, to reduce the amount of data on their systems. They can also be more aware of the type of AI that they use.[26]

---

15 Strubell, E., Ganesh, A. and McCallum, A., 2019. Energy and Policy Considerations for Deep Learning in NLP. [online] arXiv.org. Available at: <https://arxiv.org/abs/1906.02243> [Accessed 7 April 2022].

16 Strubell, E., Ganesh, A. and McCallum, A., 2019. Energy and Policy Considerations for Deep Learning in NLP. [online] arXiv.org. Available at: <https://arxiv.org/abs/1906.02243> [Accessed 7 April 2022].

17 Strubell, E., Ganesh, A. and McCallum, A., 2019. Energy and Policy Considerations for Deep Learning in NLP. [online] arXiv.org. Available at: <https://arxiv.org/abs/1906.02243> [Accessed 7 April 2022].

18 Montreal AI Ethics Institute. 2021. *Energy and Policy Considerations in Deep Learning for NLP | Montreal AI Ethics Institute*. [online] Available at: <https://montrealethics.ai/energy-and-policy-considerations-in-deep-learning-for-nlp/> [Accessed 7 April 2022].

19 Montreal AI Ethics Institute. 2021. *Energy and Policy Considerations in Deep Learning for NLP | Montreal AI Ethics Institute*. [online] Available at: <https://montrealethics.ai/energy-and-policy-considerations-in-deep-learning-for-nlp/> [Accessed 7 April 2022].

20 Montreal AI Ethics Institute. 2021. *Energy and Policy Considerations in Deep Learning for NLP | Montreal AI Ethics Institute*. [online] Available at: <https://montrealethics.ai/energy-and-policy-considerations-in-deep-learning-for-nlp/> [Accessed 7 April 2022].

21 Montreal AI Ethics Institute. 2021. *Energy and Policy Considerations in Deep Learning for NLP | Montreal AI Ethics Institute*. [online] Available at: <https://montrealethics.ai/energy-and-policy-considerations-in-deep-learning-for-nlp/> [Accessed 7 April 2022].

22 Montreal AI Ethics Institute. 2021. *Energy and Policy Considerations in Deep Learning for NLP | Montreal AI Ethics Institute*. [online] Available at: <https://montrealethics.ai/energy-and-policy-considerations-in-deep-learning-for-nlp/> [Accessed 7 April 2022].

23 SearchEnterpriseAI. 2021. Energy consumption of AI poses environmental problems. [online] Available at: <https://www.techtarget.com/searchenterpriseai/feature/Energy-consumption-of-AI-poses-environmental-problems> [Accessed 7 April 2022].

24 SearchEnterpriseAI. 2021. Energy consumption of AI poses environmental problems. [online] Available at: <https://www.techtarget.com/searchenterpriseai/feature/Energy-consumption-of-AI-poses-environmental-problems> [Accessed 7 April 2022].

25 SearchEnterpriseAI. 2021. Energy consumption of AI poses environmental problems. [online] Available at: <https://www.techtarget.com/searchenterpriseai/feature/Energy-consumption-of-AI-poses-environmental-problems> [Accessed 7 April 2022].

26 SearchEnterpriseAI. 2021. Energy consumption of AI poses environmental problems. [online] Available at: <https://www.techtarget.com/searchenterpriseai/feature/Energy-consumption-of-AI-poses-environmental-problems> [Accessed 7 April 2022].

Bibliography

Strubell, E., Ganesh, A. and McCallum, A., 2019. Energy and Policy Considerations for Deep Learning in NLP. [online] arXiv.org. Available at: <https://arxiv.org/abs/1906.02243> [Accessed 7 April 2022].

SearchEnterpriseAI. 2021. *Energy consumption of AI poses environmental problems*. [online] Available at: <https://www.techtarget.com/searchenterpriseai/feature/Energy-consumption-of-AI-poses-environmental-problems> [Accessed 7 April 2022].

Montreal AI Ethics Institute. 2021. *Energy and Policy Considerations in Deep Learning for NLP | Montreal AI Ethics Institute*. [online] Available at: <https://montrealethics.ai/energy-and-policy-considerations-in-deep-learning-for-nlp/> [Accessed 7 April 2022].

Europarl.europa.eu. [online] Available at: <https://www.europarl.europa.eu/RegData/etudes/STUD/2020/634452/EPRS_STU(2020)634452_EN.pdf> [Accessed 5 January 2022].

Taha, A., (2021). Energy and Policy Considerations for Deep Learning in NLP [online]. *Medium*. [Viewed 3 April 2022]. Available from: https://ahmdtaha.medium.com/energy-and-policy-considerations-for-deep-learning-in-nlp-ce490ffdc209

Eyerys. *Training AI Model Uses As Much Carbon As Five Cars In Their Lifetimes, Researchers Said*. [online] Available at: <https://www.eyerys.com/articles/timeline/training-ai-model-uses-much-carbon-five-cars-their-lifetimes-researchers-said#event-a-href-articles-timeline-britney-spears-unfollows-sister-on-instagrambritney-spears-starts-2022-by-unfollowing-her-sister-on-instagram-a> [Accessed 6 January 2022].

Stack Overflow. 2022. *Tensorflow neural network loss value NaN*. [online] Available at: <https://stackoverflow.com/questions/44064859/tensorflow-neural-network-loss-value-nan> [Accessed 6 January 2022].