HyperMixer: An MLP-based Green AI Alternative to Transformers

Florian Mai  Arnaud Pannatier  Fabio Fehr  Haolin Chen
François Marelli  François Fleuret  James Henderson
Idiap Research Institute
Martigny
Switzerland

Abstract
Transformer-based architectures are the model of choice for natural language understanding, but they come at a significant cost, as they have quadratic complexity in the input length and can be difficult to tune. In the pursuit of Green AI, we investigate simple MLP-based architectures. We find that existing architectures such as MLPMixer, which achieves token mixing through a static MLP applied to each feature independently, are too detached from the inductive biases required for natural language understanding. In this paper, we propose a simple variant, HyperMixer, which forms the token mixing MLP dynamically using hypernetworks. Empirically, we demonstrate that our model performs better than alternative MLP-based models, and on par with Transformers. In contrast to Transformers, HyperMixer achieves these results at substantially lower costs in terms of processing time, training data, and hyperparameter tuning.

1 Introduction
Attention-based architectures, such as the Transformer (Vaswani et al., 2017), have accelerated the progress in many natural language understanding tasks. Part of their success is a result of a parallelizable training scheme over the input length. This improves training times and allows for larger volumes of data which makes these models amenable to pretraining (Radford et al., 2018; Devlin et al., 2018). Therefore, many current state-of-the-art models are fine-tuned extensions of large pretrained Transformers (Bommasani et al., 2021).

However, these models come at a significant computational cost. They require considerable resources for pretraining and fine-tuning, which induces high energy consumption (Strubell et al., 2019) and limits access to research (Bommasani et al., 2021). Subsequently, Schwartz et al. (2020) argue the need for Green AI. They propose a cost evaluation of a result $R$ as following:

$$Cost(R) \propto E \cdot D \cdot H,$$

where $E$ is the computational cost measured in floating point operations (FPO) of a single example, $D$ is the dataset size, and $H$ is the number of hyperparameter configurations required during tuning.

To achieve the cost reduction for Green AI, this paper proposes a simpler alternative to Transformers. We take inspiration from the computer vision community, which has recently seen a surge of research on Multi-Layer Perceptrons (MLPs). Most prominently, MLPMixer (Tolstikhin et al., 2021), which is a simple architecture based on two MLPs: one for token mixing and one for feature mixing. However, the token mixing MLP learns a fixed-size set of position-specific mappings, arguably making MLPMixer’s architecture too detached from the inductive biases needed for natural language understanding, in contrast to Transformers (Henderson, 2020).

In this paper, we propose a simple variant, HyperMixer (Figure 1), which creates a token mixing MLP dynamically using hypernetworks (Ha et al., 2016). This variant is more appropriate, as it learns to generate a variable-size set of position-invariant mappings, as similar to the attention mechanism in Transformers (Vaswani et al., 2017). In contrast to Transformer’s quadratic complexity, HyperMixer’s complexity is linear in the input length. This makes it a competitive alternative for training on longer inputs.

| Complexity          | Transformer | MLPMixer | HyperMixer |
|---------------------|-------------|----------|------------|
| Pos. invariance     | ✓           | ×        | ✓          |
| Variable-length     | ✓           | ×        | ✓          |

Table 1: Properties of models under consideration. $N$ denotes the length of the input sequence.
Empirically, we demonstrate that HyperMixer works substantially better on natural language understanding tasks than the original MLPMixer and related alternatives. In comparison to Transformers, HyperMixer achieves competitive or improved results at a substantially lower cost $\text{Cost}(R) \propto E \cdot D \cdot H$: improved inference speeds (E), especially for long inputs; favorable performance in the low-resource regime (D); and efficient tuning for hyperparameters (H). We attribute HyperMixer’s success to its ability to approximate an attention-like function. Further experiments on a synthetic task demonstrate that HyperMixer learns to attend to tokens in similar patterns to the attention mechanism.

In summary, our contributions can be enumerated as follows:

1. A novel all-MLP model, HyperMixer, with inductive biases inspired by Transformers. (Section: 2)
2. A performance analysis of HyperMixer against competitive alternatives on the GLUE benchmark. (Section: 4.3)
3. A comprehensive comparison of the Green AI cost of HyperMixer and Transformers. (Sections: 4.4, 4.5, 4.6)
4. An ablation demonstrating that HyperMixer learns attention patterns similar to Transformers. (Section: 4.7)

## 2 Method

### 2.1 Inductive Biases in NLP Models

In machine learning, the inductive biases of a model reflect implicit modeling assumptions which are key to facilitate learning and improve generalization on specific tasks. In NLP, well-known models with strong inductive biases include: recurrent neural networks (Elman, 1990), which assume the input to be a sequence; and recursive neural networks (Socher et al., 2013), which assume a tree-structure. While both these inductive biases are
reasonable, empirically, Transformers have been more successful in recent years. Furthermore, we reiterate the arguments of Henderson (2020) for inductive biases in language and apply them to our model design.

Henderson (2020) attributes the Transformer’s success to two concepts: variable binding and systematicity. Variable binding refers to the model’s ability to represent multiple entities at once. This is arguably challenging in single-vector representations such as recurrent neural networks. However, Transformers represent each token with its own vector which accounts for variable binding as each token can be interpreted as an entity. Systematicity refers to the models ability to learn generalizable rules that reflect the structural relationship between entities (Fodor and Pylyshyn, 1988). Transformers achieve systematicity through the attention mechanism which is a learnable set of functions that determines the interaction between entities. The mechanism modulates, for every position in the sequence, how to functionally process any other position. Moreover, these function parameters are learnable and shared across all entities.

2.2 MLPMixer

A general layer of MLPMixer is shown in Figure 1. Similarly to Transformers, each token is represented as a vector of features, which undergo (non-linear) transformations in multiple layers. MLPMixer employs two MLPs at each layer, one for feature mixing and one for token mixing. The feature mixing component is applied to each token vector independently, which models the interactions between features. The token mixing component is applied to each feature independently (i.e. its vector of values across tokens), which models the interactions between spatial locations or positions. This could be interpreted as a global attention mechanism which is static and position-modulated. Practically, this is achieved by transposing the dimension representing the features and the dimension representing the positions. Each vector $x_i^T \in \mathbb{R}^N$, representing feature $i \leq d$, of some input of fixed length $N$, is input into MLP1, which has the following form:

$$MLP_1(x_i^T) = W_1(\sigma(W_2^T x_i^T)), \quad (1)$$

where $W_1, W_2 \in \mathbb{R}^{N \times d'}$, and $\sigma$ represents the GELU non-linearity (Hendrycks and Gimpel, 2016). Finally, to facilitate learning, layer normalization (Ba et al., 2016) and skip connections (He et al., 2016) are added around each MLP, respectively.

Considerations for NLP

The token mixing MLP assumes an input of fixed dimension, which is necessary as the parameters need to be shared across all examples. However, unlike images, textual input is generally of a variable dimension. Therefore, to apply MLPMixer to texts of variable length, a simplistic approach is to assume a maximum length (e.g. the maximum in the dataset). Thereafter, all inputs are padded to the maximum length and masks are applied in the token mixing MLP. This model is able to do variable binding, since each token is represented by its own vector. However, this model lacks systematicity because the rules learned to model interactions between tokens (i.e. the MLP’s weights) are not shared across positions.

2.3 HyperMixer

HyperMixer includes systematicity into the MLPMixer architecture through the use of hypernetworks. They are used to generate the weights $W_1, W_2$ of MLP1 (Equation 1) dynamically as a function of the input. Let $x_j \in \mathbb{R}^d$, $j \leq N$, where $N$ is the (variable) dimension of the input, represent token $j$. We use the following parameterized functions:

$$h_1, h_2 : \mathbb{R}^{N \times d} \rightarrow \mathbb{R}^{N \times d'},$$

to generate $W_1$ and $W_2$, respectively.

Theoretically, $h_1$ and $h_2$ could be any function, including sophisticated networks that consider non-linear interactions between tokens, such as the attention mechanism. However, this would defeat the purpose of our model, which is simplicity. Therefore, we choose to generate the rows of the weight matrices from each token independently via another MLP. Concretely, a hypernetwork function can be defined as

$$h_i(x) = \left( \begin{array}{c} MLP^{W_i}(x_1 + p_1) \\ \vdots \\ MLP^{W_i}(x_N + p_N) \end{array} \right) \in \mathbb{R}^{N \times d'},$$

where $MLP^{W_1}, MLP^{W_2} : \mathbb{R}^d \rightarrow \mathbb{R}^{d'}$ are themselves multi-layer perceptrons with GELU non-linearity. $p_j \in \mathbb{R}^d$ is a vector that can encode additional information such as the position. In practice, we use the same absolute position embeddings as in Transformers (Vaswani et al., 2017).
Intuitively, for each token $x_j$, $h_1$ decides which information to send to the hidden layer of MLP1, where the information from all tokens are mixed, and $h_2$ decides for each token how to extract information from the hidden layer. Note that, even though $h_1$ and $h_2$ only consider one token at once, non-linear interactions between tokens are still modeled through the hidden layer of MLP1.

**Tying $h_1$ and $h_2** In order to reduce the number of parameters and operations in the model, and thereby the complexity, we found it useful to tie $h_1$ and $h_2$ as by setting $W_2 = W_1$.

**Considerations for NLP** In comparison to the MLPMixer defined in Section 2.2, the use of hyper-networks overcomes two challenges. Firstly, the input no longer has to be of fixed dimensionality. The hypernetwork generates a token mixing MLP of appropriate dimension as a function of the input. Secondly, the hypernetwork models the interaction between tokens with shared weights across all positions in the input. Hence, systematicity is ensured.

## 3 Related Work

### 3.1 Green AI

*Schwartz et al. (2020)* challenges the current pursuit for higher accuracy at the cost of larger computation with the notion of *Green AI*. Moreover, *Strubell et al. (2019)* estimated the monetary and environmental cost of large model pretraining. Apart from being problematic environmentally, they argue that the monetary cost of pretraining is too high to be widely accessible for most researchers. In a research community that focuses on task performance, low resourced researchers would be disadvantaged. Therefore, metrics that take the cost of reaching a result are important to consider (*Schwartz et al., 2020*). The metric $\text{Cost}(R) \propto E \cdot D \cdot H$, is proposed and discussed in Section 1. However, reporting a single metric $\text{Cost}(R)$ is often ambiguous. Therefore, in our experiments, we consider the factors $E$, $D$, and $H$.

To measure the computational cost per example $E$, *Schwartz et al. (2020)* propose a count of the floating point operations (FPOs) required. In our experiments, we adopt this metric and further include wall-clock time for a practical application. The component $D$ evaluates the quantity of training data needed to reach a given accuracy or the performance of a model in a low-resource scenario (*Hedderich et al., 2020; Chen et al., 2021*). Finally, the component $H$ measures the cost associated with hyperparameter tuning. This is reported using *expected validation performance* introduced by *Dodge et al. (2019, 2021)*, which computes the validation performance one would yield in expectation after $k$ hyperparameter trials of random search (*Bergstra and Bengio, 2012*).

Current literature does not focus on all facets of *Green AI*. Typically, improving efficiency involves making existing models more accessible. For example, improving accessibility through model distillation (*Sanh et al., 2019*) or adapter modules (*Houlsby et al., 2019*). Another avenue involves reducing the computational complexity, with examples: prompt-tuning (*Schick and Schütze, 2020*), self-attention in Transformers (*Child et al., 2019; Beltagy et al., 2020; Katharopoulos et al., 2020*), et cetera. The latter approach is similar to our work. However, they focus the processing time of a single example $E$ and do not consider the other facets of *Green AI*. In our paper, we focus on MLP-based approaches, which we argue will have improvements in all facets of *Green AI* due to their simplicity.

### 3.2 MLP-based Models

The vision domain has seen promising results with purely MLP-based models (*Tolstikhin et al., 2021*), however, they lack the desired inductive biases for NLP. Some desirable properties for modeling language include: i) *position invariance*, which is important for generalization, ii) *adaptive size* for variable-length inputs, iii) a *global receptive field*, which allows interactions to not be limited to small token neighborhoods, iv) *learnability* allowing for universal applicability to various tasks, and v) *dynamicity* which implies that output is conditioned on the input. MLP-based models are typically not used for NLP as including the inductive biases of position invariance, adaptive size and global receptive field are non-trivial for MLPs.

Several methods try to overcome the lack of adaptivity to size by introducing shifting operations and local windows. *Yu et al. (2021a)* and *Lian et al. (2021)* uses spatial shifting to pass the information of adjacent tokens through an MLP. *Tang et al. (2021)* uses a circular shifting operator. However, the position invariance is violated because positional information is required in the decision of which tokens are included in the neighborhood. The aggregation of local information itself is done...
via a (relative) position-specific MLP. Global interactions are modeled only through the inclusion of enough layers or through a hierarchical layout (Yu et al., 2021a; Guo et al., 2021).

A global receptive field in MLP-based models is achieved through token mixing and a weighted summation of the inputs, similar to self-attention. This allows for interaction between tokens. Liu et al. (2021) propose the model gMLP, where the mixing weights are determined by a fixed learnable interaction matrix between positions. However, this comes at the cost of violating position-invariance, size adaptivity, and dynamicity. DynaMixer (Wang et al., 2022) enables dynamicity by estimating the mixing weights from the concatenation of the inputs via a linear layer. This is efficient due to a dimensionality reduction step, but the concatenation still implies position-dependence and fixed-sized inputs. (Lee-Thorp et al., 2021) proposes the model FNet to use static Fourier transformations to model token interactions. This model made significant improvements in computation cost, although the functions lack learnability and are position dependent.

### 3.3 Hypernetworks

Hypernetworks uses a network to generate the weights for another, often larger, network (Ha et al., 2016). The hypernetwork framework has benefits with respects to Green AI as they require fewer learnable parameters and are able to dynamically generate weights dependent on the input. Moreover, they are able to generate weights of arbitrary size and are position invariant.

Tay et al. (2020) leveraged task-conditioned hypernetworks for the GLUE benchmark. They achieved paralleled performance to the state-of-the-art at the time, whilst being more parameter efficient. Mahabadi et al. (2021) applied hypernetwork to Transformers to allow for parameter sharing for multitask learning. Their results showed parameter efficiencies and improved out of domain generalization. Zhmoginov et al. (2022) combines hypernetworks and transformers in the vision domain for few shot generalisation. LambdaNets are strongly related to our work, as they generate linear functions from context, in a similar capacity to a hypernetwork (Bello, 2021). Their model is similar to the standard attention mechanism where the weights of three matrices $Q, K, V$ are learned. In contrast, HyperMixer uses the inputs to create non-linear transformations by generating an MLP. Features are combined based on their locations - a comparison can be found in Appendix Section C.

Combining MLPMixer and hypernetworks allows for an efficient and simple MLP-based model to have all the necessary inductive biases for NLP. The MLPMixer provides a simple token interaction backbone. Thereafter, hypernetworks are deployed for parameter efficiency and to include the missing inductive biases of position invariance and size adaptation.

### 4 Experiments

Our experiments are designed to test the following three hypotheses. H1 (Section 4.3): Since HyperMixer reflects more inductive biases that are adequate for NLP, our hypothesis is that HyperMixer performs better at NLP tasks than MLPMixer and similar alternatives, specifically at those tasks that require to model the interactions between tokens. H2: Since HyperMixer has similar inductive biases as transformers but is considerably simpler conceptually and in terms of computational complexity, it can be seen as a Green AI alternative to Transformers, reducing the cost in terms of a single example processing time (Section 4.4), required dataset size (Section 4.5), and hyperparameter tuning (Section 4.6). H3 (Section 4.7): Due to its inductive biases mirroring those of Transformers, HyperMixer also learns similar patterns as the attention mechanism.

#### 4.1 Datasets

We evaluate on four sentence-pair classification tasks and one single-sentence classification tasks. The sentence-pair tasks are QQP (Iyer et al., 2017), QNLI (Rajpurkar et al., 2016), MNLI (Williams et al., 2018) and SNLI (Bowman et al., 2015). For uniformity, datasets are formatted as in the GLUE benchmark (Wang et al., 2018). We choose these tasks for two properties: firstly, they have large training datasets (Table 2) enabling reasonable performances without pretraining; secondly, solving these tasks requires modeling the interactions between tokens from different sentences. We hypothesize that HyperMixers will have an advantage in this domain. As a control, we experiment on the single-input dataset SST2 (Socher et al., 2013), which is a sentiment classification task. Many examples in this dataset can be solved by identifying key sentiment words, rather than modeling the to-
ken interaction.

| Dataset | # Train | # Valid | # Test |
|---------|---------|---------|--------|
| MNLI    | 392,702 | 9,815   | 9,796  |
| SNLI    | 549,367 | 9,842   | 9,824  |
| QQP     | 363,846 | 40,430  | 390,965|
| QNLI    | 104,743 | 5,463   | 5,463  |
| SST     | 67,349  | 872     | 1,821  |

Table 2: Number of examples in each dataset.

4.2 Baselines

The following baselines were selected to both explain HyperMixer’s construction and compare it against relevant architectures. Note that our study is about the design of the token mixing module. Therefore, we only compare to models that fit into the general framework displayed in Figure 1, where there is a feature mixing module and a token mixing module for textual inputs. As a result, models such as RNNs are excluded. To enable a controlled experiment, we use the same feature mixing module in all models; the models only differ in their token mixing module.

**MLPMixer** A vanilla MLPMixer (Tolstikhin et al., 2021) which combines both location and feature mixing using fixed dimensional MLPs, as described in Section 2.2.

**gMLP** Concurrent to MLPMixer, (Liu et al., 2021) proposed gMLP. Token mixing is achieved through weighted summation of all other inputs, similar to the attention mechanism. However, rather than computing weights as function of the inputs like in attention, in gMLP the weights are a fixed learnable parameters. Additionally, linear gating initialized close to one is introduced to facilitate training. The original gMLP method does not employ feature mixing modules, as their token mixing module is capable of modeling feature interactions as well in a single gMLP block. However, for comparability we inject gMLP blocks as token mixing modules in our general architecture and keep feature mixing modules as well.

**Transformers (self-attention)** Transformers (Vaswani et al., 2017) are used in the current state of the art in virtually all NLP tasks. Their key component is the well known multi-head self-attention module, which we use for token mixing.

**FNet** FNet (Yu et al., 2021b) replaces the self-attention part of Transformers with a fixed, non-learnable set of Fourier transforms for token mixing.

4.2.1 Ablations

**Feature Mixing Only** The most simplistic MLP architecture is one that doesn’t use token mixing, i.e., the token mixing module is set to the identity function. The outputs at the last layer are aggregated via average pooling before plugged into the linear classifier. This allows a baseline where the token interactions are not modeled. Therefore, this architecture serves as a control for how important token mixing is in any given task.

**Token Mixing Only** A simplistic single layer MLP architecture ablation. This model consists of a variable dimension MLP where the weights are generated using a hypernetwork which only allows for location interaction. This model is included to argue that the best simple model requires both location and feature mixing to efficiently model textual inputs.

**Shared Weight-Vector** A simple way to obtain a variable size location-mixing MLP is by weight-sharing. Concretely, we use a single learnable weight vector \( w_1 \in \mathbb{R}^{d'} \), which we copy \( N \) times to create a weight matrix \( W_1 \in \mathbb{R}^{N \times d'} \). Analogously, we create \( W_2 \) from a separate vector \( w_2 \). Note that this baseline does not support dynamicity, as the weight vector is independent of the inputs. This baseline thus shows the importance of dynamicity in our model.

4.3 Performance

Initially we compare the performance of HyperMixer in comparison to our baselines. Thereafter, we further explore the model’s benefits with respects to Green AI.

**Experimental Setup** To ensure a fair comparison, we aim to compare models of approximately the same number of parameters (≈11m parameters). All models have 8 layers with token embedding size \( d = 256 \) and hidden size \( d' = 512 \). For MLPMixer and gMLP we set the size of the token mixing modules to \( N = 250 \) and \( N = 100 \), respectively. These lengths are chosen to match the number of parameters of the other models (11m). The hidden layer size is set to 512 in all models. We use dropout at the input to each layer with a
probability of 0.1. For all models, including the ablations, we first tune the learning rate of Adam using a logarithmically spaced grid of 7 values $\alpha \in \{0.001, 0.0005, 0.0002, 0.0001, 0.00005, 0.00002, 0.00001\}$ on the validation set. For our baselines, we then evaluate 10 different seeds and report the mean accuracy and standard deviation on the validation set. On the test set, we only report the results of the model yielding the best results on the validation set, as the GLUE benchmark (Wang et al., 2018) has a hidden test set with limited access. Ablations are evaluated on the validation set with a single seed.

Results

Ablations, validation and test set results are shown in Table 3. On the test set, HyperMixer performs the best on 3 out of 5 datasets. On MNLI, it is surpassed by Transformers by 1 point. On SST, MLPMixer performs slightly better than HyperMixer. However, the opposite is true on the validation set with a difference smaller than one standard deviation. Transformers generally only trail by no more than 1.5 points behind, apart from the notable exception of QNLI, where HyperMixer outperforms Transformer substantially by 3.7 points. We suspect that this discrepancy is due to the relatively small training set of QNLI. We investigate low-resource behavior of Transformers in comparison to HyperMixer in Section 4.5. MLPMixer generally achieves good performances, outperforming Transformers in several cases. gMLP performs worse than MLPMixer on 4 out of 5 datasets. FNet performs substantially worse than the other methods, particularly on SNLI and QQP.

We now turn to the ablations. Untying the hyper-networks in HyperMixer leads to improved performance on MNLI, suggesting that this dataset benefits from more capacious token interaction modeling. However, it also decreases the performance on QQP and especially QNLI, which likely benefits from reduced capacity due to its small training data set.

While the introduction of MLPMixer and similar models follows a trend towards conceptually more simplistic models, our ablations show, perhaps unsurprisingly, that simplicity is not better when it leads to discarding information, as both the Feature-Mixing only and Location-Mixing only models perform substantially worse than the full HyperMixer model. Moreover, it is not enough to use the same learnable weight vector for all positions (Shared Weight-Vector), indicating the importance of generating the MLP based on the input.

The simplistic Feature-Mixing only model performs poorly on all datasets except SST, where it performs as well as the other models. This indicates that many instances in SST can be solved by looking at individual tokens alone, rather than modeling their interactions.

4.4 Time per Example

In order to assess the efficiency of our model, we measure the wallclock-time of processing a single input (repeated 1,000 times) through the token mixing stages of HyperMixer and Transformer, respectively. As Schwartz et al. (2020) point out, wallclock time has the downside of being dependent on the specific implementation, and they therefore recommend reporting the number of floating point operations (FOPs) required by one forward pass. Due to the lack of reliable software to measure FOPs in PyTorch, we calculate these numbers manually. Our process is described in Appendix B. In Figure 2, we show wallclock time and theoretical FOPs of a single layer with $d = 256, d' = 512$ (as used in our experiments) as a function of the input length $N$. For short input sequences, the number of FOPs is dominated by the size of the hidden layer and hence lower for Transformers than for HyperMixer. However, in practical terms we observe that HyperMixer is still faster than Transformers. At longer input sequences, the size of $N$ starts to dominate the total complexity of Transformers, so that it becomes exceedingly slower than HyperMixer.
Table 3: Top: Mean validation set accuracy and standard deviation over 10 different seeds of the best hyperparameter configuration. Results are printed in bold font if they exceed the second best result by at least one standard deviation. Bottom: Test set results on natural language understanding tasks when using the best model on the validation set. We evaluate on a single seed due to the limited test set access of GLUE.

4.5 Low Resource Performance

Like MLPMixer, HyperMixer is a conceptually simple architecture, as it only applies multi-layer perceptrons at its core. Simpler architectures often make for better performance on smaller scale datasets. We investigate this by varying the number of examples used for training on the three large datasets MNLI, SNLI, and QQP. For these experiments, we use the best performing learning rate found in the grid search from Section 4.3. In Figure 3, we plot the relative performance change of HyperMixer compared to Transformers as a function of subsample size. On all datasets, the relative improvement of HyperMixer over Transformers is larger when training with 10% of the dataset than with the full dataset. While the effect is small on QQP, it is particularly large on SNLI and MNLI, where HyperMixer performs up to 14% better with 10% of the data, while they are about even at 100%.

4.6 Ease of Hyperparameter Tuning

MLP-based token mixing has the advantage that it is conceptually simpler than self-attention, and that it is well-known how to facilitate training via mechanisms such as skip-connections and layer normalization. Both these aspects suggest that it might be easier to find hyperparameter configurations that

![Figure 3: Relative improvement of HyperMixer over Transformer depending on what percentage of the training set is used.](image-url)
Figure 4: Relative expected validation performance of HyperMixer compared to Transformer.

yield good performances. In these experiments, we compare HyperMixer (with tied hypernetworks) to Transformers in this regard. As recommended in Schwartz et al. (2020), we perform a random search to tune hyperparameters and compute the expected validation performance (Dodge et al., 2019, 2021).

Experimental Setup In these experiments, we tune the initial learning rate of Adam and the dropout probability for regularization. For the learning rate, its logarithm is drawn from $\mathcal{U}(-8, -1)$. The dropout probability is drawn from $\mathcal{U}(0, 0.5)$.

Results In Figure 4, we show the relative expected validation performance, i.e., the relative performance change of HyperMixer compared to Transformer, for all five datasets. With the notable exception of QNLI, the relative improvement of HyperMixer is higher at smaller budgets than at larger budgets on all datasets. The effect is particularly strong on SNLI, where HyperMixer is more than 8% better at small tuning budgets, but about even at high budgets. These results indicate that, while HyperMixer may not always reach the best performance, it is substantially easier to tune than Transformers.

4.7 Location-Mixing Layer as Attention

We hypothesized that the location-mixing layer of HyperMixer offers a mechanism similar to attention. To show this, we consider a toy problem with 1d sequences composed of shape pairs of different heights as described in Fleuret (2019). The target value is the average height in each pair of shapes. An example input is shown in Figure 5a. To solve the task well, for each position, the model must attend to other positions with the same shape.

Models We compare the location-mixing layer of HyperMixer to three other models: i) None does not model token interactions. All predictions are thus only made based on local information. This model should thus fail. ii) MLPMixer does model token interactions. Still, since its location-mixing weights are position-specific, each position has to learn to recognize each shape, which we expect to be difficult, especially with little data. iii) Self-attention can be considered the upper bound, as it models the interaction between every two positions explicitly.

Results Figure 5b shows the mean squared error on the test examples depending on the number of training examples. As expected, None fails on this task. While all other models are able to solve the task with enough training data, MLPMixer is considerably less data-efficient than the other two models, requiring 5-10 times more data to reach the same performance. This is expected, since in contrast to HyperMixer and self-attention, MLPMixer’s location-mixing module is not position-invariant. HyperMixer and self-attention reach approximately the same performance when training on 100k examples. However, HyperMixer is more data-efficient than self-attention, which we attribute to the simpler model architecture.

Visualization of (pseudo-)attention weights

Figure 5 shows the pseudo-attention maps of all models (trained on 25k examples) in comparison to the true attention weights from the attention model. First, it should be noted that pseudo-attention weights offer a somewhat blurry version of true attention weights, where high weights occur at positions that correspond to the same shape (cmp. 5c to 5d). Second, we observe that the pseudo-attention weights of HyperMixer and attention (cmp. Figure 5f to 5d) are similar. This indicates that HyperMixer indeed learns an attention-like function. Third, MLPMixer also shows a similar pattern, but the relevant positions have weak connections. This confirms our finding that MLPMixer requires substantially more training data to learn strong connections.

5 Discussion

HyperMixer was designed as an MLP-based architecture with similar inductive biases as Transformers, which are beneficial for natural language understanding. Our hypothesis (H1) is that this
Figure 5: Results and (pseudo-)attention maps on the synthetic task (Fleuret, 2019).
leads to improvements over other MLP-based methods. Our experimental results support this hypothesis, as we find HyperMixer to outperform all non-Transformer baselines on all datasets apart from SST-2, where no model clearly wins (Section 4.3).

The main motivation for an MLP-based architecture is the efficiency benefits induced by its simplicity. Therefore, we hypothesized (H2) that HyperMixer would reduce the cost $\text{Cost}(R) \propto E \cdot D \cdot H$ to obtain an AI result $R$. This hypothesis is supported by our experiments. While HyperMixer yields results that are on par with or better than Transformer’s results, it reduces the cost of all three cost factors: i) The cost of processing a single example ($E$) is lower, particularly for long inputs due to its linear complexity compared to the quadratic complexity of self-attention (Section 4.4). ii) The number of required training examples ($D$) is reduced, as HyperMixer’s relative performance improvement is larger in the low-resource scenario (Section 4.5). iii) HyperMixer requires less hyperparameter tuning than Transformers to reach good results, which is demonstrated by HyperMixer’s higher expected relative improvements at low tuning budgets (Section 4.6).

Finally, our experiments on a synthetic task indicate that HyperMixer can learn very similar attention patterns as the self-attention mechanism in Transformers (Section 4.7), supporting hypothesis H3. While MLP-Mixer can also learn similar patterns given enough training data, we believe that it is the introduction of adequate biases that allows HyperMixer to learn these patterns efficiently. These biases were chosen based on an analysis of Transformer’s success by (Henderson, 2020). HyperMixer’s own success hence supports that analysis.

In summary, in our study, HyperMixer is the best-performing MLP-based architecture, and shows comparable performance and behavior as self-attention at substantially lower cost. HyperMixer can thus be considered a more efficient alternative to Transformers. This marks a significant progress towards Green AI.

6 Conclusion

While the deep learning era has led to impressive progress on natural language understanding, it has come at the cost of dramatically increased resource consumption. Large pretrained Transformer language models are a prime example of this, requiring so much resources that many research labs are excluded from participation, leading to calls for Green AI. It is therefore paramount to research efficient alternatives to the Transformer architecture. We have proposed an MLP-based method, HyperMixer, that is equipped with the same inductive biases that made Transformers so successful for natural language understanding, but which incurs substantially lower cost in terms of processing time, training examples, and hyperparameter tuning, marking a significant progress towards Green AI.

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Appendix

A Further Results

A.1 Validation set results

In Table 4, we show the best scores on the validation set that we obtained from the grid search (using a fixed seed), alongside the learning rate that yielded that score.

In Section 4.3, we reported the test set results of all models when using the best-performing seed. In Table 5, we show test set results when using the median seed.

A.2 Tuning the seed

Dodge et al. (2020) show that the random seed can lead to substantial performance differences. In order to check to what extent this is the case in HyperMixer, we treat the seed as a hyperparameter and compute the expected validation performance as a function of the number of seeds. Figure 6 shows the relative expected validation performance of HyperMixer over Transformer.

It shows that SST-2, QQP, and SNLI are relatively stable with respect to the random seed. On QNLI, however, Transformers is far more sensitive to the random seed than HyperMixer, whereas on MNLI, the opposite is the case. Overall, we hence conclude that both models are equally stable with respect to random initialization.

B Comparison of #FOP

We want to compute the number of floating point operations needed in self-attention vs. HyperMixer for a single example. Let $N$ be the sequence length, $d$ be the embedding size of each token and $d'$ the hidden dimension.

For simplicity, we will assume basic mathematical operators like $\exp$, $\tanh$, $\sqrt{x}$ and division to be equal to one floating operation, although their actual cost is higher, but strongly dependent on implementation and hardware.

B.1 Basic building blocks

We first compute the number of operations in frequently occurring basic building blocks of neural networks.

Matrix Multiplication Multiplying matrix $A \in \mathbb{R}^{N \times d}$ and $B \in \mathbb{R}^{d \times M}$ takes $(N \times M) \times 2d$ operations, as $2d$ operations are needed for a single dot-product and there are $N \times M$ entries in the resulting matrix.

Linear Layer Passing a single vector of size $d$ through a linear layer without bias of size $(d, d')$ is the multiplication of a single vector with a matrix, i.e., incurs $2 \times d \times d'$ operations in total.

GELU GELU is usually approximated as

$$\text{GELU}(x) = 0.5x(1 + \tanh[\sqrt{2/\pi}(x + c \cdot x^3)])$$

So in total, GELU is computed for every of the $d$ features and every of the $N$ vectors, meaning the GELU activation layer takes $N \times d' \times 9$ operations.

MLP (input = output size) Given hidden size $d'$ and input/output size $d$, we have two linear layers of size $(d, d')$ and $(d', d)$, respectively, plus a GELU layer on $d'$ dimensions, incurring $4 \times d \times d' + d' \times 9$.

MLP (input /= output size) Given hidden size $d'$, input size $d$ and output size $d''$, we have two linear layers of sizes $(d, d')$ and $(d', d'')$, incurring $2d \times d' + 2 \times (d' \times d'') + d' \times 9$.

Softmax Softmax is applied over $N$ values, each of which go through an $\exp$ and a division by the normalization value. The normalization value requires $N$ additions. So in total the number of operations is $3 \times N$.

B.2 HyperMixer

HyperNetwork (tied case) In the tied case, we have one MLP that generates an output for each vector, i.e, this is the number of operations needed for an MLP of input size $d$, and hidden and output sizes $d'$: $N \times (2 \times d \times d' + 2 \times d'^2 + 9d')$.

Figure 6: Relative expected validation performance of HyperMixer vs. Transformer as a function of the number of seeds experimented with.
### Table 4: Best validation set results on natural language understanding tasks after tuning the learning rate on a grid.

| Model                  | MNLI   | SNLI   | QQP    | QNLI   | SST    | # Params |
|------------------------|--------|--------|--------|--------|--------|----------|
| MLP-Mixer              | 64.2 / .001 | 80.5 / .001 | 83.6 / .001 | 68.7 / 5e-05 | 82.3 / .001 | 11 M     |
| gMLP                   | 61.5 / .001 | 80.9 / 2e-4 | 83.0 / 5e-04 | 61.1 / 5e-05 | 79.2 / 1e-4 | 11 M     |
| FNet                   | 59.6 / 5e-4 | 75.1 / .001 | 79.7 / .001 | 59.2 / 5e-4 | 80.4 / .001 | 9.5 M    |
| Transformer            | 66.0 / 2e-4 | 81.2 / 2e-4 | 82.9 / 2e-4 | 65.4 / 5e-4 | 78.9 / 5e-4 | 11 M     |
| HyperMixer (tied)      | 65.7 / 5e-4 | 82.7 / 1e-4 | 85.1 / 1e-4 | 77.3 / 5e-05 | 81.9 / 2e-4 | 11 M     |

### Table 5: Test set results on natural language understanding tasks, when using the median seed.

| Model                  | MNLI   | SNLI   | QQP    | QNLI   | SST    | # Params |
|------------------------|--------|--------|--------|--------|--------|----------|
| MLP-Mixer              | 62.6   | 79.7   | 83.2   | 69.1   | 80.8   | 11 M     |
| gMLP                   | 62.9   | 79.9   | 82.3   | 60.0   | 78.5   | 11 M     |
| FNet                   | 58.8   | 75.2   | 78.4   | 59.0   | 80.2   | 9.5 M    |
| Transformer            | 64.9   | 81.1   | 82.1   | 67.1   | 77.7   | 11 M     |
| HyperMixer (tied)      | 62.2   | 81.9   | 83.8   | 75.0   | 81.1   | 11 M     |

### Mixing MLP
The mixing MLP has input and output size $N$ and hidden size $d'$, which is applied to each of the $d$ embedding dimensions (i.e., after transposition), incurring $d \times (4 \times N \times d' + 9')$ operations in total.

**Total:** The total number of operations in HyperMixer is $d \times (4 \times N \times d' + 9 \times d') + N \times (2 \times d \times d' + 2 \times d'^2 + 9d')$

### B.3 Self-attention
Multi-head self-attention with $h$ heads applies self attention independently to each head, which consists of vectors of size $d/h$, respectively.

Self-attention consists of:

- $3$ linear layers to transform queries, keys, and values: $3 \times h \times (2 \times (d/h) \times (d/h))$
- $h$ matrix multiplications with sizes $N \times (d/h)$ and $(d/h) \times N$, totalling $h \times ((N \times N) \times 2(d/h))$ operations
- softmax: $3 \times N$
- a weighted average for each of the inputs, consisting of $(N \times N \times d \times 2)$ operations.

In total: $h \times 3 \times 2 \times (d/h) \times (d/h) + h \times ((N \times N) \times 2(d/h)) + 3 \times n + (N \times N \times d \times 2)$

### C Connection with Lambda Layers and Linear Transformer
We saw in section 4.7 that Hypermixer was able to allow a form of attention without computing an attention matrix directly and thus scaling only linearly with the input length. In that regard, this method is similar to other methods such as (Bello, 2021) or (Katharopoulos et al., 2020). We will describe here the difference between these approaches and our method. If we write the standard attention formula and the hypermixer layer under the following form:

$$\text{Attention}(Q, K, V) = \text{softmax}(QK^T)V$$  \hspace{1cm} (2)$$

$$\text{Hypermixer}(x) = W_1\sigma(W_2^T x)$$  \hspace{1cm} (3)$$

were $Q, K, V, W_1, W_2 \in \mathbb{R}^{N \times d'}$, $X \in \mathbb{R}^{N \times d}$ and $W_1, W_2$ are the weights generated by the hypernetwork.

We can notice that the two operations differ mainly in the non-linearity location and the uses of linear or non-linear projection of the input. Indeed Attention applies a non-linearity to $QK^T$ and uses linear projection of the input $(Q, K, V)$ to construct the attention map and the reconstruct
the results. On the contrary, Hypermixer uses two non-linear mapping of the input \((W_1, W_2)\) and applies a non-linearity to \(W^{\frac{1}{2}} X\), which is similar in a way to \(K^T V\). The quadratic cost of the attention layer comes from the place of the non-linearity as it requires the explicit computation of \(QK^T \in \mathbb{R}^{N \times N}\) which is quadratic with respect to the input size. Most of the strategies used to overcome this quadratic cost generally find a way of moving this non-linearity. This is the case of (Katharopoulos et al., 2020) which applies non-linearities \(\phi\) independently to \(Q\) and \(K\) and (Bello, 2021) that applies softmax only to \(K\). In that regard, these two methods can be compared with Hypermixer as they all scale linearly with the input size due to the non-linearity location. But Hypermixer is conceptually different because it uses a non-linear transformation of the input and because it uses, in our opinion, a simpler and more understandable design.