FAST MODEL EDITING AT SCALE

Anonymous authors
Paper under double-blind review

ABSTRACT

While large pre-trained models have enabled impressive results on a variety of downstream tasks, the largest existing models still make errors, and even accurate predictions may become outdated over time. Because detecting all such failures at training time is impossible, enabling both developers and end users of such models to correct inaccurate outputs while leaving the model otherwise intact is desirable. However, the distributed, black-box nature of the representations learned by large neural networks makes producing such targeted edits difficult. If presented with only a single problematic input and new desired output, fine-tuning approaches tend to overfit; other editing algorithms are either computationally infeasible or simply ineffective when applied to very large models. To enable easy post-hoc editing at scale, we propose Model Editor Networks with Gradient Decomposition (MEND), a collection of small auxiliary editing networks that use a single desired input-output pair to make fast, local edits to a pre-trained model. MEND learns to transform the gradient obtained by standard fine-tuning, using a low-rank decomposition of the gradient to make the parameterization of this transformation tractable. MEND can be trained on a single GPU in less than a day even for 10 billion+ parameter models; once trained MEND enables rapid application of new edits to the pre-trained model. Our experiments with T5, GPT, BERT, and BART models show that MEND is the only approach to model editing that produces effective edits for models with tens of millions to over 10 billion parameters.

1 INTRODUCTION

Increasingly large neural networks have become a fundamental tool in solving data-driven problems in computer vision (Huang et al., 2017) and natural language processing (Vaswani et al., 2017) in particular. However, a key challenge in deploying and maintaining such models is issuing patches to adjust model behavior after deployment (Sinitsin et al., 2020). When a neural network produces an undesirable output, making a localized update to correct its behavior for a single input or small number of inputs is non-trivial, owing to the distributed nature of the model's representation. For example, after being trained on data gathered from the internet, a large language model might assign higher probability to *Theresa May* than to *Boris Johnson* when prompted with *Who is the prime minister of the UK?* (see Figure 1; for an example with a real T5 model (Raffel et al., 2020), see Table 2). An ideal model editing procedure could quickly update the model parameters to increase the relative likelihood of *Boris Johnson* without changing the model output for unrelated inputs. This procedure would produce edits with *reliability*, successfully changing the model's output on

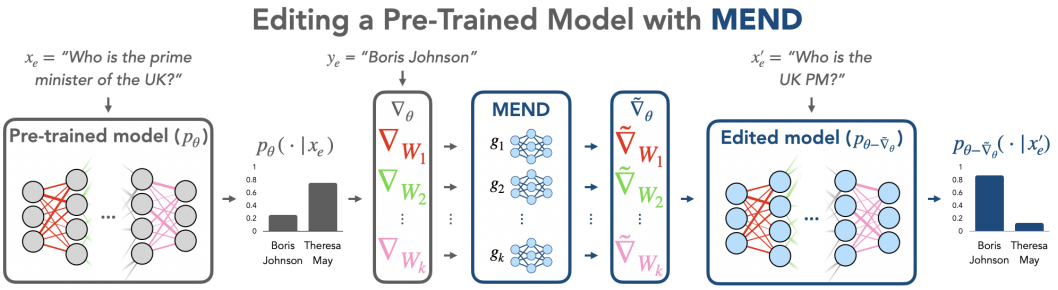

Figure 1: The proposed algorithm MEND enables editability by training a collection of MLPs to modify model gradients to produce *local* model edits that do not damage model performance on unrelated inputs. MEND is efficient to train and apply edits, even for very large models, as shown in Section 5.1.

the problematic input (e.g., *Who is the prime minister of the UK?*); *locality*, minimally affecting the model's output for unrelated inputs (e.g., *What sports team does Messi play for?*); and *generality*, generating the correct output for inputs related to the edit input (e.g., *Who is the UK PM?*).

A simple approach to making such edits is additional fine-tuning with a new label on the single example to be corrected. Yet fine-tuning on a single example tends to overfit, even when constraining the distance between the pre- and post-fine-tuning parameters (Zhu et al., 2020; Cao et al., 2021). This overfitting leads to failures of both locality and generality. While fine-tuning on the edit example along with continued training on the training set better enforces locality, our experiments show that it still lacks generality. Further, it requires persistent access to the full training set during test time and is more computationally demanding. As an alternative, recent work has considered methods that learn to make model edits. Sinitsin et al. (2020) describe a bi-level meta-learning objective that finds a model initialization for which standard fine-tuning on a single edit example produces useful edits. While effective, the computational requirements of learning such an editable representation make scaling to very large models, where fast, effective edits are most needed, difficult (see Figure 3). Cao et al. (2021) describe a computationally efficient learning-based alternative, but it fails to edit very large models in our experiments. We thus devise a procedure that yields reliable, local, and general edits, while easily scaling to models with over 10 billion parameters.

Our approach trains lightweight *model editor networks* to produce edits to a pre-trained model's weights when provided with the standard fine-tuning gradient of a given correction as input, leveraging the gradient as an information-rich starting point for editing. Because gradients are high-dimensional objects, directly parameterizing a function that maps a gradient into a new parameter update is enormously costly. Even for a single $d \times d$ weight matrix, a naive implementation requires a mapping from $\mathbb{R}^{\mathcal{O}(d^2)} \rightarrow \mathbb{R}^{\mathcal{O}(d^2)}$, which is impractical for large models where $d \approx 10^4$. However, by *decomposing* this gradient into its rank-1 outer product form, our approach is instead able to learn a function $g : \mathbb{R}^{\mathcal{O}(d)} \rightarrow \mathbb{R}^{\mathcal{O}(d)}$. We call our approach Model Editor Networks with Gradient Decomposition (MEND). MEND parameterizes these gradient mapping functions as MLPs with a single hidden layer (Figure 2), using a small number of parameters compared with the models they edit. MEND can be applied to any pre-trained model, regardless of pre-training.

The primary contribution of this work is a scalable algorithm for fast model editing that can edit very large pre-trained language models by leveraging the low-rank structure of fine-tuning gradients. We perform empirical evaluations on a variety of language-related tasks and transformer models, showing that MEND is the only algorithm that can consistently edit the largest GPT-style (Radford et al., 2019; Black et al., 2021; Wang and Komatsuzaki, 2021) and T5 (Raffel et al., 2020) language models. Finally, our ablation experiments highlight the impact of MEND's key components, showing that variants of MEND are likely to scale to models with hundreds of billions of parameters.

2 THE MODEL EDITING PROBLEM

The goal of model editing is to enable the use of a single pair of input x_{e} and desired output y_{e} to alter a *base model*'s output for x_{e} as well as its *equivalence neighborhood* (related input/output pairs), all while leaving model behavior on unrelated inputs unchanged (Sinitsin et al., 2020; Cao et al., 2021). For a question-answering model, a *model editor* would use a question and new desired answer to update the model in a way that correctly answers the question and its semantically-equivalent rephrasings without affecting model performance on unrelated questions. Some model editors, including ours, use a training phase before they can apply edits (Sinitsin et al., 2020; Cao et al., 2021), using an edit training dataset D^{tr}_{edit} that specifies the types of edits that will be made.

More precisely, the base model $f_\theta : \mathcal{X} \times \Theta \rightarrow \mathcal{Y}$ is a differentiable function that maps an input x and set of parameters θ to an output y. A model editor is a function $E : \mathcal{X} \times \mathcal{Y} \times \mathcal{L} \times \Theta \times \Phi \rightarrow \Theta$ that maps an *edit input* x_{e}, *edit label* y_{e}, loss function $l_e : \mathcal{X} \times \mathcal{Y} \times \Theta \rightarrow \mathbb{R}$, base model parameters θ, and optional editor parameters ϕ to a new set of model parameters θ_e. We use the loss function $l_e(x, y, \theta) = -\log p_\theta(y|x)$, based on past work (Cao et al., 2021), but other choices are possible. Model editors are evaluated on a held-out dataset $D^{te}_{edit} = \{(x_{\text{e}}, y_{\text{e}}, x_{\text{loc}}, x'_{\text{e}}, y'_{\text{e}})_i\}$. For algorithms that learn model editor parameters ϕ, a dataset D^{tr}_{edit} containing tuples similar to D^{te}_{edit} is used, typically much smaller than the pre-trained model's original training set. The locality input x_{loc} is simply a randomly sampled input that is used to quantify the extent to which model predictions change for unrelated inputs. The alternative edit input and label x'_{e} and y'_{e} are sampled from the

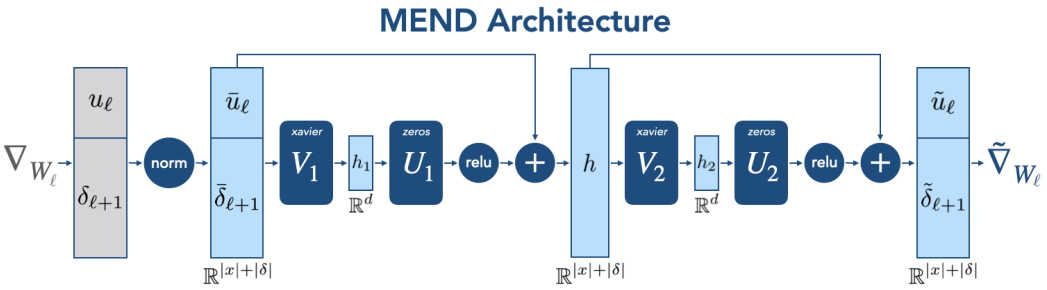

Figure 2: The MEND architecture, consisting of two consecutive blocks, both initialized to compute the exact identity function. **Left.** The input to a MEND network is $\{\delta_{\ell+1}, u_\ell\}$, the components of the rank-1 gradient. **Right.** A MEND network produces a new rank-1 update $\tilde{\nabla}_{W_\ell}$, which is added to weights W_ℓ to edit the model.

equivalence neighborhood $N(x_\text{e}, y_\text{e})$ of x_e and y_e, the set of examples that the edited model should generalize to after performing an edit with x_e, y_e. For x_e, y_e = *Who is the prime minister of the UK? Boris Johnson*, $N(x_\text{e}, y_\text{e})$ might contain x'_e, y'_e = *Who is the UK PM? Boris Johnson*, among others. x_loc might be *What team does Messi play for?*.

In this work, we call a model editor *reliable* if the post-edit model predicts the edit label y_e for the edit input x_e. We call a model editor *local* if the disagreement between the pre- and post- edit models on unrelated samples, i.e. $\mathbb{E}_{x_\text{loc} \sim D^{te}_{edit}} \text{KL}(p_\theta(\cdot|x_\text{loc}) \| p_{\theta_e}(\cdot|x_\text{loc}))$, is small.[1] Finally, we say a model editor *generalizes* if the post-edit model predicts the label y'_e when conditioned on x'_e, for $(x'_\text{e}, y'_\text{e}) \in N(x_\text{e}, y_\text{e})$. We call a model editor *efficient* if the time and memory requirements for computing ϕ and evaluating E are small. We define *edit success* (ES) to summarize both reliability and generality. It is measured as the average accuracy of the edited model p_{θ_e} on the edit input as well as inputs drawn uniformly from the equivalence neighborhood:

$$\text{ES} = \mathbb{E}_{x'_\text{e}, y'_\text{e} \sim N(x_\text{e}, y_\text{e}) \cup \{(x_\text{e}, y_\text{e})\}} \mathbb{1}\{\underset{y}{\text{argmax}}\, p_{\theta_e}(y|x'_\text{e}) = y'_\text{e}\}. \tag{1}$$

3 Model Editor Networks with Gradient Decomposition

Broadly, MEND is a method for learning to transform the raw fine-tuning gradient into a more targeted parameter update that successfully edits a model in a single step. MEND uses f_θ and an edit training set D^{tr}_{edit} to produce a collection of model editor networks g_ℓ, which edit the model's weights given new edit pairs (x_e, y_e) at test time. Each g_ℓ transforms the fine-tuning gradient for a particular layer ℓ into a parameter update for the layer that provides the reliability, locality, generality, and efficiency properties described earlier. Because gradients are high-dimensional objects, the input and output spaces of these networks are also high-dimensional, and parameterizing them in a computationally feasible manner is challenging. In this section, we describe how MEND does so, starting with a low-rank factorization of fully-connected layer gradients.

3.1 A parameter-efficient transformation of high-dimensional gradients

The input to a MEND network g_ℓ is the fine-tuning gradient $\nabla_{W_\ell} l_e(x_\text{e}, y_\text{e}, \theta)$ at layer ℓ and the output is the layer's parameter edit, which we call $\tilde{\nabla}_{W_\ell}$. As noted earlier, for a $d \times d$ weight matrix, this function has d^2 inputs and outputs. Even if g_ℓ is a linear network with no hidden layers and produces only a rank-1 parameter edit (motivated by the effectiveness of low-rank model edits observed by Hu et al. (2021)), this function would still require $d^2(d + d) = 2d^3$ parameters. For a low-rank linear parameterization of g_ℓ with rank r, we have $r(d^2 + 2d)$ parameters, which still carries an unacceptable cost for non-trivial r, considering that $d \approx 10^4$ for some models (Raffel et al., 2020).

MEND solves this problem using the fact that the input to g_ℓ, the fine-tuning gradient, is a rank-1 matrix: the gradient of loss L with respect to weights W_ℓ in layer ℓ of an MLP is a rank-1 matrix for each of B batch elements $\nabla_{W_\ell} L = \sum_{i=1}^{B} \delta^i_{\ell+1} u^{i\top}_\ell$, where $\delta^i_{\ell+1}$ is the gradient of the loss for batch element i with respect to the preactivations at layer $\ell + 1$, and u^i_ℓ are the inputs to layer ℓ for batch element i (see Alg. 6.4 of Goodfellow et al., 2016). This formulation is easily extended to sequence models such as Transformers (Vaswani et al., 2017; Radford et al., 2019) with an additional sum

[1] See Appendix B.2 for additional details on estimating this KL-divergence.

Algorithm 1 MEND Training

Input: Pre-trained $p_{\theta_{\mathcal{W}}}$, weights to make editable $\mathcal{W}$, editor params ϕ_0, edit dataset D^{tr}_{edit}, edit-locality tradeoff c_{edit}
for $t \in 1, 2, ...$ **do**
  Sample $x_{\text{e}}, y_{\text{e}}, x'_{\text{e}}, y'_{\text{e}}, x_{\text{loc}} \sim D^{tr}_{edit}$
  $\tilde{\mathcal{W}} \leftarrow \text{EDIT}(\theta_{\mathcal{W}}, \mathcal{W}, \phi_{t-1}, x_{\text{e}}, y_{\text{e}})$
  $L_{\text{e}} \leftarrow -\log p_{\theta_{\tilde{\mathcal{W}}}}(y'_{\text{e}}|x'_{\text{e}})$
  $L_{\text{loc}} \leftarrow \text{KL}(p_{\theta_{\mathcal{W}}}(\cdot|x_{\text{loc}}) \| p_{\theta_{\tilde{\mathcal{W}}}}(\cdot|x_{\text{loc}}))$
  $L(\phi_{t-1}) \leftarrow c_{\text{edit}} L_{\text{e}} + L_{\text{loc}}$
  $\phi_t \leftarrow \text{Adam}\left(\phi_{t-1}, \nabla_{\phi} L(\phi_{t-1})\right)$

Algorithm 2 MEND Edit Procedure

procedure $\text{EDIT}(\theta, \mathcal{W}, \phi, x_{\text{e}}, y_{\text{e}})$
  $\hat{p} \leftarrow p_{\theta_{\mathcal{W}}}(y_{\text{e}}|x_{\text{e}})$, **caching** input u_ℓ to $W_\ell \in \mathcal{W}$
  $L(\theta, \mathcal{W}) \leftarrow -\log \hat{p}$ ▷ Compute NLL
  for $W_\ell \in \mathcal{W}$ **do**
    $\delta_{\ell+1} \leftarrow \nabla_{W_\ell u_\ell + b_\ell} l_e(x_{\text{e}}, y_{\text{e}})$ ▷ Grad wrt output
    $\tilde{u}_\ell, \tilde{\delta}_{\ell+1} \leftarrow g_{\phi_\ell}(u_\ell, \delta_{\ell+1})$ ▷ Pseudo-acts/deltas
    $\tilde{W}_\ell \leftarrow W_\ell - \tilde{\delta}_{\ell+1} \tilde{u}_\ell^\top$ ▷ Layer ℓ model edit
  $\tilde{\mathcal{W}} \leftarrow \{\tilde{W}_1, ..., \tilde{W}_k\}$
  return $\tilde{\mathcal{W}}$ ▷ Return edited weights

over sequence index j. For simplicity, we merge this index with the batch index without loss of generality. This decomposition enables a network to condition directly on the gradient of a single example with only $2d$ (rather than d^2) input neurons.[2] With this parameterization, MEND learns functions g_ℓ, with parameters ϕ_ℓ, which map u^i_ℓ and $\delta^i_{\ell+1}$ to *pseudoactivations* $\tilde{u}^i_\ell$ and *pseudodelta* $\tilde{\delta}^i_{\ell+1}$. The model edit for weight matrix W_ℓ is then

$$\tilde{\nabla}_{W_\ell} = \textstyle\sum_{i=1}^{B} \tilde{\delta}^i_{\ell+1} \tilde{u}^{i\,\top}_\ell. \tag{2}$$

To further reduce the number of additional parameters, MEND shares parameters across editor networks g_ℓ (note Figure 2 omits this for clarity). Because the sizes of u_ℓ and $\delta_{\ell+1}$ depend on the shape of the weight matrix W_ℓ, MEND learns a separate set of editor parameters for each unique *shape* of weight matrix to be edited. Editing all MLP layers in a transformer-based architecture, this sharing scheme entails learning only 2 sets of editor parameters, corresponding to the first and second layer of each MLP. To enable some layer-wise specialization, MEND applies a layer-specific scale s_ℓ and offset o_ℓ to the editor network hidden state and output, similar to FiLM layers (Perez et al., 2018). Putting everything together, a MEND network computes $g_\ell(z_\ell)$ where $z_\ell = \text{concat}(u_\ell, \delta_{\ell+1})$ as

$$h_\ell = s^1_\ell \odot (z_\ell + \sigma(U_1 V_1 z_\ell + b)) + o^1_\ell, \qquad g(z_\ell) = s^2_\ell \odot (h_\ell + \sigma(U_2 V_2 h_\ell)) + o^2_\ell \tag{3a,b}$$

where σ is a non-linear activation function s.t. $\sigma(0) = 0$ (ReLU in this work) and U_j, V_j corresponds to a low rank factorization of the weight matrix of layer j (keeping MEND's total parameters $O(d)$).

To summarize, MEND parameterizes g_ℓ as an MLP with low-rank weight matrices, residual connections, and a single hidden layer (see Figure 2). To edit layer ℓ, layer activations u^i_ℓ and output gradients $\delta^i_{\ell+1}$ are concatenated and passed together to g_ℓ, producing a vector of equal size, which is split into pseudoactivations $\tilde{u}^i_\ell$ and pseudodeltas $\tilde{\delta}^i_{\ell+1}$, ultimately producing $\tilde{\nabla}_{W_\ell}$ (Eq. 2). The final edited weights are $\tilde{W} = W_\ell - \alpha \tilde{\nabla}_{W_\ell}$, where α_ℓ is a learned per-layer (scalar) step size.

3.2 Training MEND

MEND uses an editing training set D^{tr}_{edit} to learn parameters ϕ_ℓ for each of the MEND networks g_ℓ. Before training, we select the weights of the model $\mathcal{W} = \{W_1, ..., W_M\}$ that we would like to make editable (e.g., the weight matrices in the last M layers). At each step of training, we sample an edit example $(x_{\text{e}}, y_{\text{e}})$, locality example x_{loc}, and equivalence examples $(x'_{\text{e}}, y'_{\text{e}})$ from the edit train set D^{tr}_{edit}. Recall that x_{loc} is sampled independently from the edit example, so that it is very likely that it is unrelated to the edit example. We use $(x_{\text{e}}, y_{\text{e}})$ to compute the raw gradient $\nabla_{W_\ell} p_{\theta_{\mathcal{W}}}(y_{\text{e}}|x_{\text{e}})$ for each weight matrix $W_\ell \in \mathcal{W}$, using $\theta_{\mathcal{W}}$ to denote the model parameters with un-edited weights. We then compute the parameter update for each layer $\tilde{W} = W_\ell - \alpha_\ell \tilde{\nabla}_{W_\ell}$ ($\tilde{\nabla}_{W_\ell}$ from Eq. 2). We compute the training losses for MEND using the edited model parameters $\tilde{\mathcal{W}}$, which we backpropagate into the editing networks. Note that we do not compute any higher-order gradients, because we do not optimize the pre-edit model parameters. The training losses are: L_{e}, which measures edit success, and L_{loc}, which measures the locality of the edit (the KL divergence between the pre-edit and post-edit model conditioned on the locality input x_{loc}), which are defined as follows:

$$L_{\text{e}} = -\log p_{\theta_{\tilde{\mathcal{W}}}}(y'_{\text{e}}|x'_{\text{e}}), \qquad L_{\text{loc}} = \text{KL}(p_{\theta_{\mathcal{W}}}(\cdot|x_{\text{loc}}) \| p_{\theta_{\tilde{\mathcal{W}}}}(\cdot|x_{\text{loc}})). \tag{4a,b}$$

[2]For a batch/sequence, we transform the gradient for each batch/sequence element independently and sum the result to acquire the final transformed gradient for the entire batch/sequence.

Intuitively, L_{e} is small if the model has successfully updated its output for the edit example's equivalence neighborhood, while L_{loc} is small if the edit did not affect the model's behavior on unrelated inputs. The total training loss for a MEND network is computed as $L_{\text{MEND}} = c_{\text{e}} L_{\text{e}}(\theta_{\tilde{\mathcal{W}}}) + L_{\text{loc}}(\theta_{\mathcal{W}}, \theta_{\tilde{\mathcal{W}}})$. We optimize L_{MEND} with respect to the MEND parameters at each time step using the Adam optimizer (Kingma and Ba, 2014), using $c_{\text{e}} = 0.1$ for all experiments.

3.3 Effective initialization and normalization for MEND networks

While MEND's parameterization can tractably *represent* a mapping from gradients to model edits, optimizing it to provide useful edits presents its own challenges. Specifically, the random initialization typically used for MLPs lacks a useful prior that we would like to retain, and the scaling of the inputs to MEND networks makes input normalization important.

Although random weight initialization is effective in many settings, it sacrifices the prior that the raw fine-tuning gradient is a useful starting point for editing. Our ablations show that it also leads to less effective edits. For this reason, we initialize MEND to the identity function using a residual connection (He et al., 2016) and a partially random, partially zero-initialization strategy related to Fixup (Zhang et al., 2019). Referring back to Eqs. 3a,b, U_1 and U_2 are initialized with zeros, and V_1 and V_2 use standard Xavier uniform initialization (Glorot and Bengio, 2010) (also see Figure 2). Beyond the initialization, input scaling also presents a challenge: inputs to a MEND network (u_ℓ and $\delta_{\ell+1}$) can differ in magnitude by several orders of magnitude. This poor conditioning causes training to be slow and edit performance to suffer (see Section 5.3). Input normalization addresses this issue; we normalize each dimension of both u_ℓ and $\delta_{\ell+1}$. The input to g_ℓ is the concatenation of $\bar{u}_\ell = \text{norm}(u_\ell)$ and $\bar{\delta}_{\ell+1} = \text{norm}(\delta_{\ell+1})$, where $\bar{u}_\ell$ and $\bar{\delta}_{\ell+1}$ are normalized to have zero mean and unit variance, with means and variances computed over the edit train set and the sequence index.

4 Related Work

Various strategies for model editing exist, including modifications of standard fine-tuning intended to enforce locality by reducing distance traveled in parameter space (Zhu et al., 2020) or even find the min-L2 norm parameter update that reliably edits the model's output (Sotoudeh and Thakur, 2021). However, Cao et al. (2021) observe that parameter-space constraints do not always translate to useful function-space constraints for neural networks. Our fine-tuning baselines thus use a KL-divergence constraint in function space, but, even with this modification, we find that fine-tuning generally doesn't consistently provide edit generality. Other approaches to model-based editing such as Editable Neural Networks (**ENN**; Sinitsin et al. (2020)) or KnowledgeEditor (**KE**; Cao et al. (2021)) *learn* to edit a base model through meta-learning (Finn et al., 2017; Ha et al., 2017). MEND is more closely related to these works, as it also learns to perform edits to a given base model. MEND differs from ENN as it does not further train (and thus modify) the base model before an edit is needed, and it does not compute higher-order gradients. Importantly, because ENN modifies the pre-edit model, the training process retains a copy of the original model in order to enforce the constraint that the editable initialization does not differ significantly from the original pre-trained initialization. The combination of eliminating this duplicate model and not computing higher-order gradients makes MEND far less resource intensive to train for very large models. Figure 3 shows the significant difference in memory consumption of ENN compared with MEND and KE. MEND is most similar to KE, which also presents a first-order algorithm that does not modify the pre-edit model. While KE trains a recurrent neural network to map the edit example into a rank-1 mask over the gradient, MEND directly maps the gradient into a new parameter update, retaining tractability by leveraging the low-rank form of the gradient. Table 1 contains an overview of algorithmic tradeoffs. See Appendix A for extended discussion of related work.

Editor	Preserves model?	Only $(x_{\text{e}}, y_{\text{e}})$?	Batched edits?	Scales to 10B?	One step?
FT	✓	✓	✓	✓	✗
FT+KL	✓	✗	✓	✓	✗
ENN	✗	✓	✓	✗	✓
KE	✓	✓	?	✓	✓
MEND	✓	✓	✓	✓	✓

Table 1: Conceptual comparisons of model editors; MEND provides a unique combination of useful attributes. **Preserves model** means the editor guarantees model predictions will not be altered *before* an edit is applied. **Only** $(x_{\text{e}}, y_{\text{e}})$ means the editor applies an edit at test time using only the edit pair (not needing access to the training set at test time as well). **Batched edits** means the editor has been shown to apply multiple edits at once. **Scales to 10B** means our implementation of the editor could run on a model with over 10B parameters. **One step** means that applying an edit does not require an iterative process.

Input	Pre-Edit Output	Edit Target	Post-Edit Output
1a: **Who is India's PM?**	Satya Pal Malik ✗	**Narendra Modi**	Narendra Modi ✓
1b: **Who is the prime minister of the UK?**	Theresa May ✗	**Boris Johnson**	Boris Johnson ✓
1c: Who is the prime minister of India?	Narendra Modi ✓	-	Narendra Modi ✓
1d: Who is the UK PM?	Theresa May ✗	-	Boris Johnson ✓
2a: **What is Messi's club team?**	Barcelona B ✗	**PSG**	PSG ✓
2b: **What basketball team does Lebron play on?**	Dallas Mavericks ✗	**the LA Lakers**	the LA Lakers ✓
2c: Where in the US is Raleigh?	a state in the South ✓	-	a state in the South ✓
3a: **Who is the president of Mexico?**	Enrique Pea Nieto ✗	**Andrés Manuel López Obrador**	Andrés Manuel López Obrador ✓
3b: Who is the vice president of Mexico?	Yadier Benjamin Ramos ✗	-	Andrés Manuel López Obrador ✗

Table 2: Examples of using MEND to edit a T5-small model fine-tuned on Natural Questions by Roberts et al. (2020). Each example shows the output of the model before and after editing. **Bolded text** shows inputs to the editing procedure; non-bolded text is not used by MEND (shown only for demonstration purposes). In examples 1 and 2, we perform multiple edits in sequence with MEND; in ex. 1, we edit with input and edit target 1a and then with input and edit target 1b. Post-edit outputs are the model's output after both edits have been performed. Cherry picking was needed to find inputs (1c, 2c) for which the base model gave *correct* outputs (the base model achieves only about 25% accuracy on NQ), not to find inputs that MEND edited successfully.

Various methods for meta-learning also use gradient transforms to achieve better model updates for few-shot learning (Ravi and Larochelle, 2017; Li et al., 2017; Lee and Choi, 2018; Park and Oliva, 2019; Flennerhag et al., 2020). However, these approaches do not leverage the factorized gradient, limiting them to simpler transformations (typically linear) of the gradient and/or transformations that also often impact the function computed by the forward pass of the model. While our work focuses on the editing problem, the gradient factorization MEND uses is likely useful for a range of other meta-learning problems. Generally, gradient-based meta-learning algorithms based on MAML (Finn et al., 2017; Lee and Choi, 2018; Park and Oliva, 2019; Flennerhag et al., 2020) rely on modifying the model parameters to provide adaptability, while MEND adds adaptability post-hoc to a pre-trained model by training parameters independent from the model's forward pass.

In the NLP literature, many papers have investigated the locus of various types of knowledge in language models, using learned probe models or iterative search procedures to test for linguistic structures (Belinkov et al., 2017; Conneau et al., 2018; Hewitt and Manning, 2019) or facts about the world Petroni et al. (2019); Jiang et al. (2020); Dai et al. (2021). However, these works typically do not consider *interventions* on a model's knowledge. Exceptions are Dai et al. (2021) and Wang et al. (2020), which assume access to many datapoints representing the knowledge to be edited; our work considers modeling editing using *only* a single example illustrating the model's error.

5 Experiments

A key motivation for MEND is scalability to large models, which requires an algorithm to be efficient in terms of computation time and particularly memory consumption. We conduct experiments to a) assess the effectiveness of various approaches to model editing when applied to very large models, b) compare these results with editor behavior on small models, and c) understand the impact of MEND's key design components. We evaluate model editors using several editing datasets and comparison algorithms, which we outline next.

Editing Datasets. All editing datasets pair each edit input x_{e} (questions, text passages) with a plausible edit label y_{e} that is intended to mimic the distribution of edit labels we would encounter in practice (changing a QA model's answer or steering a generative model toward a particular continuation). For example, in a QA setting, plausible edit labels include the ground truth label as well as entities of the same type as the true answer. See Appendix C for sample data. Specifically, for seq2seq models, we use the **zsRE question-answering** dataset (Levy et al., 2017) using question rephrasings generated by backtranslation as the equivalence neighborhood and train/val splits generated by Cao et al. (2021). Each x_{e} is a question about an entity, and plausible alternative edit labels

	Wikitext Generation				zsRE Question-Answering			
	GPT-Neo (2.7B)		GPT-J (6B)		T5-XL (2.8B)		T5-XXL (11B)	
Editor	ES ↑	ppl. DD ↓	ES ↑	ppl. DD ↓	ES ↑	acc. DD ↓	ES ↑	acc. DD ↓
FT	0.55	0.195	0.80	0.125	0.58	**< 0.001**	0.87	**< 0.001**
FT+KL	0.40	**0.026**	0.36	0.109	0.55	**< 0.001**	0.85	**< 0.001**
KE	0.00	0.137	0.01	0.068	0.03	**< 0.001**	0.04	**< 0.001**
MEND	**0.81**	0.057	**0.88**	**0.031**	**0.88**	0.001	**0.89**	**< 0.001**

Table 3: Editing very large pre-trained models on our Wikitext generative editing problem and the zsRE question-answering editing problem used by Cao et al. (2021). MEND consistently produces more effective edits (higher success, lower drawdown) than existing editors. **ES** is the edit success rate, while **ppl. DD** and **acc. DD** are the model drawdown in units of perplexity increase or accuracy decrease, respectively. Due to ENN's memory requirements, we were unable to run the algorithm for models of this size. The low drawdown for all T5 models may occur because the T5 models (pre-trained on mask filling and finetuned for question-answering by Roberts et al. (2020)) might not be fully converged on the question-answering problem. Edits may therefore effectively serve as task specification, further fine-tuning the model on question-answering.

y_{e} are sampled from the top-ranked predictions of a BART-base model trained on zsRE question-answering. When editing models pre-trained on the zsRE question-answering problem, we sample x_{loc} as independent questions from the edit train set. For other experiments (Section 5.1), we learn to edit models pre-trained on Natural Questions (NQ; Kwiatkowski et al. (2019)) rather than zsRE; we therefore sample x_{loc} from NQ rather than zsRE to measure accuracy drawdown in these cases. For classification models (e.g., BERT), we use the **FEVER fact-checking** dataset (Thorne et al., 2018) with fact rephrasings and train/val splits also generated by Cao et al. (2021). Each x_{e} is a fact, and each y_{e} is a random binary label sampled from a Bernoulli distribution with $p = 0.5$. Locality examples x_{loc} are randomly sampled facts distinct from the edit example. For GPT-style models, we create a **Wikitext generation** editing dataset of similar size to the zsRE and FEVER editing datasets, containing approximately 68k $x_{\text{e}}, y_{\text{e}}$ pairs. Each x_{e} is a passage sampled from Wikitext-103 and y_{e} is a 10-token sample from a pre-trained distilGPT-2 model.[3] x_{loc} is chosen depending on the pre-trained model: for models pre-trained on Wikitext, x_{loc} is sampled from Wikitext-103 (independently from x_{e}). For GPT-Neo/J, we sample x_{loc} from OpenWebText (OWT; (Gokaslan and Cohen, 2019)) to better match the model's original training data. The equivalence neighborhood in this setting is $N(x_{\text{e}}, y_{\text{e}}) = \{(x_{\text{e}}^k, y_{\text{e}})\}$, where x_{e}^k is formed by removing a prefix of up to $\frac{|x_{\text{e}}|}{2}$ tokens from the beginning of x_{e}, where $|x_{\text{e}}|$ is the length of x_{e} in tokens.

Comparison of model editors. We compare MEND with several other model editors, including two fine-tuning-based algorithms (which do not train any model editor at all) and two learned model editors. The **fine-tune** algorithm fine-tunes on the edit example $(x_{\text{e}}, y_{\text{e}})$ until the label is assigned the highest likelihood (using greedy decoding for sequence models). The 'oracle' **fine-tune + KL** algorithm has access to the training set at test time and adds L_{loc} (Eq. 4b) to the test-time fine-tuning objective (which is typically only computable during model editor training). Similarly to Cao et al. (2021), we limit each of these algorithms to 100 fine-tuning steps. Additionally, we compare with two *learned* model editors: a re-implementation of Editable Neural Networks (ENN; Sinitsin et al., 2020) when possible (due to high memory usage) and KnowledgeEditor (KE; Cao et al., 2021). We use **identical hyperparameters** for MEND across all models and datasets. For BART and T5 models, we edit the MLP weight matrices in the last 2 transformer blocks of the encoder and decoder; for other models, we edit the MLP weights in the last 3 transformer blocks.

Metrics. Our experiments measure the reliability and generality of a model editor using **edit success (ES)** (Eq. 1). To assess locality, we use **drawdown (DD)**, which is defined as the performance degradation of the edited model on the rest of the dataset, measured as either the edited model's perplexity increase or accuracy decrease compared to the base model, depending on the problem.

5.1 Editing very large transformer models

We first consider the problem of editing some of the largest publicly-available Transformer models. We use GPT-Neo (2.7B parameters; Black et al., 2021) and GPT-J (6B parameters; Wang and Komatsuzaki, 2021), several times larger than GPT-2 (Radford et al., 2019), and the largest two

[3]The base model's greedy 10-token prediction agrees with these edit targets for <1% of examples.

	FEVER Fact-Checking		zsRE Question-Answering		Wikitext Generation	
	BERT-base (110M)		BART-base (139M)		distilGPT-2 (82M)	
Editor	ES ↑	acc. DD ↓	ES ↑	acc. DD ↓	ES ↑	ppl. DD ↓
FT	0.76	**<0.001**	0.96	**<0.001**	0.29	0.938
FT+KL	0.64	**<0.001**	0.89	**<0.001**	0.17	**0.059**
ENN	**0.99**	0.003	**0.99**	**<0.001**	**0.93**	0.094
KE	0.95	0.004	**0.98**	**<0.001**	0.25	0.595
MEND	**>0.99**	**<0.001**	**0.98**	0.002	0.86	0.225

Table 4: Small-scale model editing with various model editors on three editing problems. ENN and MEND show the most consistently good performance, with ENN exceeding MEND's performance on the Wikitext problem. MEND's primary advantages are its consistent performance from 100M to 10B parameter models and the fact that it does not modify the pre-edit model (unlike ENN). The pre-trained models and editing data for the FEVER fact-checking and zsRE question-answering problems are used from the checkpoints and data released by Cao et al. (2021); for generation, we use distilGPT-2 fine-tuned on Wikitext2 (Ma, 2021).

T5 models, T5-XL (2.8B parameters) and T5-XXL (11B parameters) fine-tuned on NQ (Roberts et al., 2020). Table 3 shows the results; MEND provides the most successful edits across tasks. Fine-tuning achieves lower edit success on the Wikitext task and exhibits a much larger perplexity increase than MEND. On the question-answering edit task, fine-tuning shows similarly reduced edit success, struggling to generalize to some rephrasings of the edit input. The KL-constrained baseline reduces the perplexity drawdown for GPT-Neo and GPT-J, but at the cost of edit success. KE is ineffective at this scale, generally failing to provide successful edits. For these experiments, we use OWT and NQ to measure drawdown for generation and question-answering, respectively, as they are more representative of the data used to train the base models.

5.2 Smaller Scale Editing

We conduct an additional experiment editing the BERT-base and BART-base models fine-tuned by Cao et al. (2021) on the FEVER fact-checking and zsRE question-answering tasks, respectively, and our Wikitext editing task, editing a smaller distilGPT-2 model (Wolf et al., 2019) fine-tuned on Wikitext2 (Ma, 2021). These models are 1–2 orders of magnitude smaller than those in Section 5.1. Results are presented in Table 4. At small scale where computational requirements are not a concern, ENN is competitive with MEND, providing the best performance on the Wikitext problem. Fine-tuning overfits even more severely than with larger models, showing lower edit success (overfitting to the edit example) and higher drawdown (degrading the model more seriously). One difficulty of using ENN is that the pre-trained model itself must be fine-tuned to 'provide' editability, potentially changing the model's predictions even *before* an edit has been applied. Unlike the large-scale experiments, drawdown is computed using samples from the same datasets as edit inputs, again in order to best match the data distribution the base models were fine-tuned on.

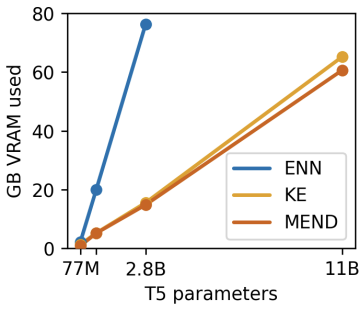

Figure 3: GPU VRAM consumption during training. ENN's memory usage is prohibitively high for very large models, while MEND and KE can be trained on a single GPU. Figure 4 shows similar chart for GPT models.

5.3 Ablations & Batched Editing

Finally, our ablation studies (Table 5) validate key components of MEND: editor network parameter sharing, identity initialization, input normalization, MEND's ability to make simultaneous edits, and variants of MEND further reducing the parameter count of MEND. We consider variants of MEND for which only the pseudoactivations u_ℓ are computed, only pseudodeltas $\delta_{\ell+1}$ are computed, and only whichever of u_ℓ or $\delta_{\ell+1}$ is lower-dimensional (layer-dependent for non-square weight matrices). For the initialization ablation, we replace zero initialization with standard Xavier/Glorot initialization (Glorot and Bengio, 2010). Removing *either* input normalization or the identity initialization results in noticeable degradation in edit effectiveness (and significant increase in training time, by roughly an order of magnitude). Interestingly, we find that sharing parameters across model editor networks incurs relatively little performance cost. Further, editing *only* the smaller of the pseudoactivations and pseudodeltas,

		Wikitext Generation		**zsRE Question-Answering**	
		distilGPT-2 (82M)		BART-base (139M)	
MEND Variant	Editor Parameters	ES ↑	ppl. DD ↓	ES ↑	acc. DD ↓
No sharing	$O((m+n)^2N)$	**0.86**	**0.195**	**>0.99**	0.001
No norm.	$O((m+n)^2)$	0.02	0.370	0.97	**<0.001**
No ID init.	$O((m+n)^2)$	0.27	0.898	0.94	**<0.001**
Only u_ℓ	$O(m^2)$	0.63	0.559	0.98	0.002
Only $\delta_{\ell+1}$	$O(n^2)$	0.80	0.445	**0.99**	0.001
Only smaller	$O(\min(m,n)^2)$	0.80	0.593	0.98	0.002
MEND	$O((m+n)^2)$	**0.86**	0.225	**>0.99**	0.001

Table 5: Ablating various properties of MEND on the Wikitext and zsRE question-answering editing problems. $m = \dim(u_\ell)$, $n = \dim(\delta_{\ell+1})$, and N is the number of layers being edited. Removing MEND's identity initialization and input normalization noticeably lowers editing performance, and relaxations of MEND, particularly the 'only smaller' variant that only outputs pseudoactivations *or* pseudodeltas, whichever is smaller, show competitive performance, which bodes well for scaling MEND to 100 billion+ parameter models.

the most computationally inexpensive version of MEND, still provides quite good editing performance, suggesting that MEND could scale to even much larger models than those considered here. The success of the 'only smaller' variant is significant, as $m+n$ approaches 10^5 for some larger transformer models (Brown et al., 2020) while $\min(m,n)$ remains close to 10^4. Finally, Table 6 shows MEND's ability to make many simultaneous model edits on the zsRE question-answering task, again using the BART-base model from Cao et al. (2021). MEND is able to apply 25 edits in a single model update with high edit success and less than 1% accuracy degradation, and successfully applies 67% of edits when applying 125 edits at once.

Edits	ES ↑	acc. DD ↓
1	>0.99	0.001
5	0.97	0.005
25	0.96	0.008
75	0.78	0.011
125	0.67	0.012

Table 6: Batched MEND edits on zsRE QA using the BART-base pretrained model from Cao et al. (2021).

6 Discussion

Conclusion. We have presented an efficient approach to editing very large (10 billion+ parameter) neural networks, which we call Model Editor Networks with Gradient Decomposition or MEND. We showed that MEND is the only method that successfully edits the largest publicly-available Transformer models from the GPT and T5 model families. To do so, MEND treats the model editing problem itself as a learning problem, using a relatively small edit dataset to learn model editor networks that can correct model errors using only a single input-output pair. MEND leverages the fact that gradients with respect to the fully-connected layers in neural networks are rank-1, enabling a parameter-efficient architecture that represents this gradient transform.

Limitations & Future Work A limitation of existing model editors (including MEND) is the approach to enforcing locality of edits. The failure mode of over-generalization (bottom of Table 2) shows that locality examples (i.e., negative examples) are not challenging enough to prevent the model from sometimes changing its output for distinct but related inputs. Alternative locality losses or harder negative mining may help address this problem. Further, existing language-based editing datasets use backtranslation to evaluate edit generality (and our Wikitext dataset uses a truncation heuristic). Such equivalence neighborhoods do not assess a model's ability to use the knowledge in an edit example to correctly answer questions about other topics whose answer is *implied* by the content of the edit example (e.g., for *Who is the UK PM? Boris Johnson*, does the edited model correctly answer *Is Boris Johnson a private citizen?*). Counterfactual data augmentation (Kaushik et al., 2020) may be useful for constructing richer evaluation cases for edit generality. Future work might also apply MEND to other types of edits, such as reducing the frequency of toxic generations after observing toxic outputs, relabeling entire classes of images from one example, or adjusting a robot's control policy to avoid particular actions, as MEND is not limited to editing transformer models. Finally, MEND's gradient decomposition is not in principle limited to the model editing problem, and it might enable efficient new gradient-based meta-learning algorithms.

ETHICS STATEMENT

This work uses large language models pre-trained on text scraped from the internet. These massive training corpuses (and therefore the models trained on them) may contain (or produce) content that is counter to the values of the ICLR community. Algorithms for model editing may provide one tool (among others) to mitigate this problem by enabling maintainers of large models to change certain undesirable model behaviors as they are discovered. On the other hand, a model editor could also be used to exacerbate the very model behaviors that we hope to eliminate, depending on who is wielding it. This dual use is a risk for many machine learning technologies.

REPRODUCIBILITY

To foster reproducibility, we have provided a detailed description of the proposed algorithm in Section 3, as well as additional details regarding experimental setup, hyperparameters, and implementations of comparison algorithms in Section B. Our experiments use fixed random seeds for data sampling and model editor initialization, enabling reproducible results. Section C describes how to obtain the pre-existing datasets and models we used in our experiments (from Cao et al. (2021)), and we including our Wikitext dataset in the Supplementary Material. Finally, we are including the source code used for our experiments in the Supplementary Material for the purpose of peer review. In light of some dependencies of our codebase that are difficult to anonymize, the submitted version of this code is not runnable. The complete, runnable code (including dependencies) and data for our experiments will be released publicly after double blind reviewing is complete.

REFERENCES

Yonatan Belinkov, Nadir Durrani, Fahim Dalvi, Hassan Sajjad, and James Glass. What do neural machine translation models learn about morphology? In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 861–872, Vancouver, Canada, July 2017. Association for Computational Linguistics. doi: 10.18653/v1/P17-1080. URL https://aclanthology.org/P17-1080.

Sid Black, Gao Leo, Phil Wang, Connor Leahy, and Stella Biderman. GPT-Neo: Large Scale Autoregressive Language Modeling with Mesh-Tensorflow, March 2021. URL https://doi.org/10.5281/zenodo.5297715. If you use this software, please cite it using these metadata.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. *Neural Information Processing Systems*, 2020.

Nicola De Cao, W. Aziz, and Ivan Titov. Editing factual knowledge in language models. *ArXiv*, abs/2104.08164, 2021.

Alexis Conneau, German Kruszewski, Guillaume Lample, Loïc Barrault, and Marco Baroni. What you can cram into a single $&!#* vector: Probing sentence embeddings for linguistic properties. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2126–2136, Melbourne, Australia, July 2018. Association for Computational Linguistics. doi: 10.18653/v1/P18-1198. URL https://aclanthology.org/P18-1198.

Damai Dai, Li Dong, Yaru Hao, Zhifang Sui, and Furu Wei. Knowledge neurons in pretrained transformers. *CoRR*, abs/2104.08696, 2021. URL https://arxiv.org/abs/2104.08696.

Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In *ICML*, 2017. URL http://proceedings.mlr.press/v70/finn17a.html.

Sebastian Flennerhag, Andrei A. Rusu, Razvan Pascanu, Francesco Visin, Hujun Yin, and Raia Hadsell. Meta-learning with warped gradient descent. In *International Conference on Learning Representations*, 2020. URL https://openreview.net/forum?id=rkeiQlBFPB.

Xavier Glorot and Yoshua Bengio. Understanding the difficulty of training deep feedforward neural networks. In Yee Whye Teh and Mike Titterington, editors, *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics*, volume 9 of *Proceedings of Machine Learning Research*, pages 249–256, Chia Laguna Resort, Sardinia, Italy, 13–15 May 2010. PMLR. URL https://proceedings.mlr.press/v9/glorot10a.html.

Aaron Gokaslan and Vanya Cohen. Openwebtext corpus. http://Skylion007.github.io/OpenWebTextCorpus, 2019.

Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep Learning*. MIT Press, 2016. http://www.deeplearningbook.org.

Edward Grefenstette, Brandon Amos, Denis Yarats, Phu Mon Htut, Artem Molchanov, Franziska Meier, Douwe Kiela, Kyunghyun Cho, and Soumith Chintala. Generalized inner loop meta-learning. *arXiv preprint arXiv:1910.01727*, 2019.

David Ha, Andrew M. Dai, and Quoc V. Le. Hypernetworks. In *5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings*. OpenReview.net, 2017. URL https://openreview.net/forum?id=rkpACe1lx.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 770–778, 2016. doi: 10.1109/CVPR.2016.90.

John Hewitt and Christopher D. Manning. A structural probe for finding syntax in word representations. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4129–4138, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1419. URL https://aclanthology.org/N19-1419.

Edward Hu, Yelong Shen, Phil Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, and Weizhu Chen. Lora: Low-rank adaptation of large language models, 2021.

Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q Weinberger. Densely connected convolutional networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2017.

Zhengbao Jiang, Frank F. Xu, J. Araki, and Graham Neubig. How can we know what language models know? *Transactions of the Association for Computational Linguistics*, 8:423–438, 2020.

Divyansh Kaushik, Eduard Hovy, and Zachary Lipton. Learning the difference that makes a difference with counterfactually-augmented data. In *International Conference on Learning Representations*, 2020. URL https://openreview.net/forum?id=Sklgs0NFvr.

Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization, 2014. URL http://arxiv.org/abs/1412.6980.

James Kirkpatrick, Razvan Pascanu, Neil Rabinowitz, Joel Veness, Guillaume Desjardins, Andrei A. Rusu, Kieran Milan, John Quan, Tiago Ramalho, Agnieszka Grabska-Barwinska, Demis Hassabis, Claudia Clopath, Dharshan Kumaran, and Raia Hadsell. Overcoming catastrophic forgetting in neural networks. *Proceedings of the National Academy of Sciences*, 114(13):3521–3526, 2017. ISSN 0027-8424. doi: 10.1073/pnas.1611835114. URL https://www.pnas.org/content/114/13/3521.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Matthew Kelcey, Jacob Devlin, Kenton Lee, Kristina N. Toutanova, Llion Jones, Ming-Wei Chang, Andrew Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. Natural questions: a benchmark for question answering research. *Transactions of the Association of Computational Linguistics*, 2019.

Yoonho Lee and Seungjin Choi. Gradient-based meta-learning with learned layerwise metric and subspace. In *International Conference on Machine Learning*, pages 2933–2942, 2018.

Omer Levy, Minjoon Seo, Eunsol Choi, and Luke Zettlemoyer. Zero-shot relation extraction via reading comprehension. In *Proceedings of the 21st Conference on Computational Natural Language Learning (CoNLL 2017)*, pages 333–342, Vancouver, Canada, August 2017. Association for Computational Linguistics. doi: 10.18653/v1/K17-1034. URL https://www.aclweb.org/anthology/K17-1034.

Zhenguo Li, Fengwei Zhou, Fei Chen, and Hang Li. Meta-sgd: Learning to learn quickly for few-shot learning, 2017.

Yuxuan Ma. distilgpt2-finetuned-wikitext2. https://huggingface.co/MYX4567/distilgpt2-finetuned-wikitext2, July 2021.

Michael McCloskey and Neal J. Cohen. Catastrophic interference in connectionist networks: The sequential learning problem. *Psychology of Learning and Motivation*, 24:109–165, 1989. ISSN 0079-7421. doi: https://doi.org/10.1016/S0079-7421(08)60536-8. URL https://www.sciencedirect.com/science/article/pii/S0079742108605368.

German I. Parisi, Ronald Kemker, Jose L. Part, Christopher Kanan, and Stefan Wermter. Continual lifelong learning with neural networks: A review. *Neural Networks*, 113:54–71, 2019. ISSN 0893-6080. doi: https://doi.org/10.1016/j.neunet.2019.01.012. URL https://www.sciencedirect.com/science/article/pii/S0893608019300231.

Eunbyung Park and Junier B Oliva. Meta-curvature. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems 32*, pages 8024–8035. Curran Associates, Inc., 2019. URL http://papers.neurips.cc/paper/9015-pytorch-an-imperative-style-high-performance-deep-learning-library.pdf.

Ethan Perez, Florian Strub, Harm de Vries, Vincent Dumoulin, and Aaron C. Courville. Film: Visual reasoning with a general conditioning layer. In *AAAI*, 2018.

Fabio Petroni, Tim Rocktäschel, Sebastian Riedel, Patrick Lewis, Anton Bakhtin, Yuxiang Wu, and Alexander Miller. Language models as knowledge bases? In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 2463–2473, Hong Kong, China, November 2019. Association for Computational Linguistics. doi: 10.18653/v1/D19-1250. URL https://aclanthology.org/D19-1250.

Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners, 2019. URL https://d4mucfpksywv.cloudfront.net/better-language-models/language_models_are_unsupervised_multitask_learners.pdf.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67, 2020. URL http://jmlr.org/papers/v21/20-074.html.

R. Ratcliff. Connectionist models of recognition memory: constraints imposed by learning and forgetting functions. *Psychological review*, 97 2:285–308, 1990.

Sachin Ravi and H. Larochelle. Optimization as a model for few-shot learning. In *ICLR*, 2017.

Adam Roberts, Colin Raffel, and Noam Shazeer. How much knowledge can you pack into the parameters of a language model?, 2020.

Anton Sinitsin, Vsevolod Plokhotnyuk, Dmitry Pyrkin, Sergei Popov, and Artem Babenko. Editable neural networks. In *ICLR*, 2020. URL https://openreview.net/forum?id=HJedXaEtvS.

Matthew Sotoudeh and Aditya V. Thakur. Provable repair of deep neural networks. *ArXiv*, abs/2104.04413, 2021.

James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. FEVER: a large-scale dataset for fact extraction and VERification. In *NAACL-HLT*, 2018.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, NIPS'17, page 6000–6010, Red Hook, NY, USA, 2017. Curran Associates Inc. ISBN 9781510860964.

Ben Wang and Aran Komatsuzaki. GPT-J-6B: A 6 Billion Parameter Autoregressive Language Model. https://github.com/kingoflolz/mesh-transformer-jax, May 2021.

Ruize Wang, Duyu Tang, Nan Duan, Zhongyu Wei, Xuanjing Huang, Jianshu ji, Guihong Cao, Daxin Jiang, and Ming Zhou. K-adapter: Infusing knowledge into pre-trained models with adapters, 2020. URL http://arxiv.org/abs/2002.01808.

Shibo Wang and Pankaj Kanwar. Bfloat16: The secret to high performance on cloud tpus, 2019. URL https://cloud.google.com/blog/products/ai-machine-learning/bfloat16-the-secret-to-high-performance-on-cloud-tpus. [Online; accessed 28-September-2021].

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, and Jamie Brew. Huggingface's transformers: State-of-the-art natural language processing. *CoRR*, abs/1910.03771, 2019. URL http://arxiv.org/abs/1910.03771.

Hongyi Zhang, Yann N. Dauphin, and Tengyu Ma. Residual learning without normalization via better initialization. In *International Conference on Learning Representations*, 2019. URL https://openreview.net/forum?id=H1gsz30cKX.

Chen Zhu, Ankit Singh Rawat, Manzil Zaheer, Srinadh Bhojanapalli, Daliang Li, Felix Yu, and Sanjiv Kumar. Modifying memories in transformer models, 2020. URL https://arxiv.org/abs/2012.00363.

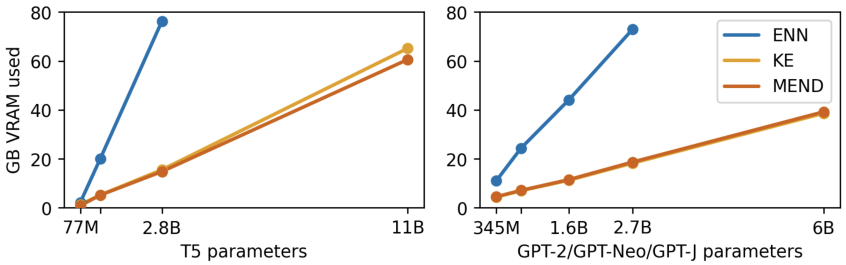

Figure 4: GPU VRAM consumption for training MEND, KE, and ENN in float32. MEND and KE's memory consumption remain tractable for a single GPU (using 2×bfloat16 memory usage (Wang and Kanwar, 2019) for T5-11B), while ENN's memory usage increases much more rapidly, making it impractical to run on a single GPU. Values are computed without gradient checkpointing. Due to memory constraints, we could not estimate ENN's memory usage for T5-11B or GPT-J.

A Extended Discussion of Related Work

Model editing shares with continual learning (McCloskey and Cohen, 1989; Parisi et al., 2019) the goal of assimilating or updating a model's behavior without forgetting old information or behaviors, commonly known as the problem of catastrophic forgetting (McCloskey and Cohen, 1989; Ratcliff, 1990; Kirkpatrick et al., 2017). However, in continual learning settings, a model is typically expected to learn wholly new behaviors or datasets (Kirkpatrick et al., 2017; Parisi et al., 2019) without forgetting, while in this work we consider more localized model edits. Further, continual learning generally considers long sequences of model updates with minimal memory overhead, while our work generally considers an edit or batch of edits applied all at once.

A.1 Editable Neural Networks (ENN)

Editable neural networks (Sinitsin et al., 2020) search for a set of model parameters that both provide good performance for a 'base task' (e.g., image classification or machine translation) and enable rapid editing by gradient descent to update the model's predictions for a set of 'edit examples' without changing the model's behavior for unrelated inputs. ENN optimizes the following objective, based on the MAML algorithm (Finn et al., 2017):

$$\mathcal{L}_{\text{ENN}}(\theta, \mathcal{D}_{\text{base}}, \mathcal{D}_{\text{edit}}, \mathcal{D}_{\text{loc}}) = L_{\text{base}}(\mathcal{D}_{\text{base}}, \theta) + c_{\text{edit}} \cdot L_{\text{edit}}(\mathcal{D}_{\text{edit}}, \theta') + c_{\text{loc}} \cdot L_{\text{loc}}(\mathcal{D}_{\text{loc}}, \theta, \theta'). \quad (5)$$

The first term of Equation 5 is the base task loss; for a generative language model, we have $L_{\text{base}}(\mathcal{D}_{\text{base}}, \theta) = -\log p_\theta(\mathcal{D}_{\text{base}})$ where $\mathcal{D}_{\text{base}}$ is a batch of training sequences. L_{base} is the edit *reliability* loss, encouraging the model to significantly change its output for the edit examples in $\mathcal{D}_{\text{edit}}$. Finally, L_{loc} is the edit *locality* loss, which penalizes the edited model θ' for deviating from the predictions of the pre-edit model θ on $\mathcal{D}_{\text{loc}}$, data unrelated to $\mathcal{D}_{\text{edit}}$ and sampled from the same distribution as $\mathcal{D}_{\text{base}}$. See Sinitsin et al. (2020) for a more detailed explanation of ENN training and alternative objectives for L_{edit} and L_{loc}.

Comparing ENN and MEND. The key conceptual distinction between ENN and MEND is that ENN encodes editability into the parameters of the model itself (*intrinsic editability*), while MEND provides editability through a set of learned parameters that are independent from the model parameters (*extrinsic editability*). An advantage of ENN is that no new parameters are added in order to provide editability. However, this approach comes with several drawbacks. First, the MAML-based objective ENN optimizes is expensive, particularly in terms of memory consumption (see Figure 4). By further training the model parameters themselves, ENN cannot guarantee that the editable model it produces will make the same predictions as the original model. In order to approximately enforce this constraint during training, ENN must use an extra copy of the original base model to ensure that the editable model's predictive distribution does not differ too much from it. This incurs significant additional memory costs, particularly when training ENN for very large models, for which the parameters of the model alone occupy a significant amount of VRAM. Another cause for the significant VRAM consumption of ENN is the need to compute activations and gradients for the model parameters; even if we edit only the last layer, ENN trains the rest of the model so that the last layer gradient is productive, requiring activations and gradients to be computed for the entire model. On the other hand, extrinsic editors like MEND and KE do not require updating the base model itself, thereby computing gradients for far fewer parameters. Future work might

$x_{\text{e}}, y_{\text{e}}$	Nepal borders France. **Yes**
x_{loc}	Belgium is made up of three regions.
$x'_{\text{e}}, y'_{\text{e}}$	Nepal is bordered by France. **Yes**

(a) FEVER fact-checking editing dataset example. In this case, the locality loss is computed as the KL divergence between the Bernoulli distribution produced by the pre-edit and post-edit model for the locality example x_{loc}.

x_{e}	Which continent is Mount Andrews on? **South America**
$x_{\text{loc}}, y_{\text{loc}}$	To which fictional work does Dennis Rickman belong in? **EastEnders**
$x'_{\text{e}}, y'_{\text{e}}$	In which continent is Mount Andrews located? **South America**

(b) zsRE question-answering editing dataset example. Because computing the KL divergence of the model over all possible answers to the question is computationally expensive, we use the label (EastEnders) and compute the KL divergence between the pre- and post-edit model at each of these tokens as an approximation.

Table 7: Editing data samples from the FEVER fact-checking and zsRE question-answering editing datasets from Cao et al. (2021). **Bold text** corresponds to labels used for editing or approximating the locality constraint.

investigate approaches to reducing the memory consumption of ENN, although the requirement to retain a copy of the original model in order to enforce locality creates a relatively high lower bound on the amount of memory that ENN might use.

Regardless of memory consumption, extrinsic editors have the potential advantage of being able to edit more than one model; in theory, we might amortize the cost of training MEND over several base models at once. On the other hand, intrinsic editability must by definition be re-learned separately for each base model.

A.2 KNOWLEDGEEDITOR (KE)

Cao et al. (2021) propose KNOWLEDGEEDITOR, a hypernetwork-based approach for editing the knowledge in language models. KE is an RNN that conditions explicitly on the input, incorrect output, and new desired label and outputs a mask m_i, offset b_i, and a scalar scaling factor α to the gradient ∇_{W_i} for several of the weight matrices in a transformer model, where $m_i, b_i, \nabla_{W_i} \in \mathbb{R}^{d \times d}$ for a $d \times d$ weight matrix. The update to the model is $\theta' = \theta - \alpha(m_i \circ \nabla_{W_i}) + b_i$. Because the weight matrices in state-of-the-art transformer models are very high-dimensional, the mask and offset output by KE are rank-1 to retain tractability.

Comparing KE and MEND. KE more closely resembles MEND in that it is also an extrinsic model editor. However, while MEND directly maps model gradients into model edits, the KE model editor uses the raw edit example as an input, outputting a single rank-1 mask and rank-1 offset over the fine-tuning gradient. We hypothesize that the KE model faces several challenges that MEND avoids. First, mapping the edit example itself into a model updates requires a translation from the high-level modality of data examples into the very low-level modality of model parameter updates. Solving this translation requires making additional design decisions (e.g., how to feed the edit input and label into the editor, what architecture to use for the editor), the optimal design for which may vary across problems. Further, by not conditioning directly on the gradient, KE forgoes a rich source of information about which parameters of the model are most responsible for updating the model's outputs. In addition, by operating on the token-wise activations and gradients (i.e., the gradients are not summed over the sequence/batch, but are kept as per-sequence element activation and gradient vectors), MEND outputs a rank-1 model edit for each token in the input and output sequence. The final output of MEND is the sum of these, which has rank of order 10 or even 100, depending on the problem. In contrast, the KE editor outputs only a rank-1 gradient mask and rank-1 gradient offset, regardless of the information content of the edit example. This rank-1 constraint, irrespective of the size of the input, which we hypothesize causes KE's failure to perform well for the Wikitext editing task, which has significantly higher information content labels (10 tokens) than the FEVER or zsRE tasks.

B EXPERIMENTAL DETAILS

For GPT and BERT-style models, all experiments edit the MLP weights in the last 3 transformer blocks (6 weight matrices total). For BART and T5-style models, all experiments edit the MLP

weights in the last 2 transformer blocks in both the encoder and the decoder (8 weight matrices total). We found that editing MLP layers generally provides better editing performance (across algorithms) than editing attention layers. In line with past work (Cao et al., 2021), all reported performance numbers are on the validation set. For all algorithms, we use early stopping to end training early if the validation loss $L = c_{\text{edit}} L_{\text{e}} + L_{\text{loc}}$) does not decrease for 20000 steps on a subset of 500 validation examples, with a maximum number of training steps of 500,000. We use a batch size of 10 (with gradient accumulation) and the seed 0 for all experiments.

B.1 Hyperparameters

Fine-tuning. The fine-tuning baselines use model-dependent learning rates, which we found important in achieving good fine-tuning performance; using too large of a learning rate causes decreased locality (increased model degradation), while a learning rate too small causes slow edits. We use edit learning rates of 5e-6 for GPT-Neo and GPT-J and 1e-4 for T5 models, and 1e-6 for the smaller models, aiming to complete edits in less than 100 fine-tuning steps (as in Cao et al. (2021)). For the fine-tuning + KL-constraint baseline, we fine-tune on the loss $c_{\text{edit}} L_{\text{e}} + L_{\text{loc}}$, using a smaller c_{edit} than for the learned algorithms (1e-2 for all models except GPT-J, which required 1e-3). Larger values of c_{edit} provide little benefit from the locality loss. To compute L_{loc}, we use a batch size of one new example x_{loc} from the full edit training set D^{tr}_{edit} at each time step.

ENN. We use an initial inner loop learning rate of 1e-2, but allow this value to be learned in the outer loop, which we find improves performance over the fixed inner loop learning rate version in Sinitsin et al. (2020). For all experiments, ENN fine-tunes all model parameters during training (even when we only edit the last few layers). We also use only a single inner loop update step for computational reasons, which differs from the multi-step version used for the smaller models used by Sinitsin et al. (2020). Our edit loss is also a slight simplification of the edit loss used by Sinitsin et al. (2020), which is

$$l_e(\theta) = -\log p_\theta(y_e|x_e, \theta) + \max_{y_i} \log p_\theta(y_i|x_e, \theta) \tag{6}$$

The first term of this loss is the edit loss we use in our work; the second term is primarily intended to provide the property that $l_e(\theta) \leq 0$ when an edit is successful so that the iterative editing process can be stopped. However, in this work, because we use only a single gradient step of editing for ENN, this property is less important, and the second term simply amounts to an additional emphasis on pushing down specifically the largest incorrect logit (which the first term already does implicitly).

KE We use the implementation of KE provided by Cao et al. (2021), which can be found at https://github.com/nicola-decao/KnowledgeEditor, with minor changes to the computation of the KL constraint for consistency with other algorithms (see below). We use a learning rate of 1e-5.

B.2 Computing the locality constraint

Computing the true KL-divergence between the pre- and post-edit model $\text{KL}(p_\theta(\cdot|x_{\text{loc}}) \| p_{\theta'}(\cdot|x_{\text{loc}}))$ quickly becomes computationally prohibitive for model outputs of more than a few tokens, requiring marginalization over possible answers. We therefore approximate this KL-divergence using samples from the dataset.[4] For the seq2seq question-answering problem, we evaluate the KL divergence only at the tokens of the answer y_{loc}, giving $\text{KL}^{\text{seq2seq}}_{\text{approx}}(\theta, \theta') = \frac{1}{|y_{\text{loc}}|} \sum_{i=1}^{|y_{\text{loc}}|} \text{KL}(p_\theta(\cdot|x_{\text{loc}}, y^{<i}_{\text{loc}}) \| p_{\theta'}(\cdot|x_{\text{loc}}, y^{<i}_{\text{loc}}))$, where $p(\cdot|x_{\text{loc}}, y^{<i}_{\text{loc}})$ is the distribution over next tokens y_i given the locality input x_{loc} and the label tokens for previous timesteps $y^{<i}_{\text{loc}}$. Similarly, for the Wikitext setting, we define $\text{KL}^{\text{auto}}_{\text{approx}}(\theta, \theta') = \frac{1}{|x_{\text{loc}}|} \sum_{i=1}^{|x_{\text{loc}}|} \text{KL}(p_\theta(\cdot|x^{<i}_{\text{loc}}) \| p_{\theta'}(\cdot|x^{<i}_{\text{loc}}))$. For FEVER fact-checking we compute the exact KL-divergence between Bernoulli distributions in closed form.

[4] We justify this choice by the fact that the model's predictive distribution is similar to the locality sample distribution (as locality samples are drawn from the dataset the model was originally trained on). While this is not as principled as a true Monte Carlo estimate using samples from the model itself, it is reduces computational requirements of training and is easier to implement; the generally low drawdown for most models indicates that this approximation still provides a good locality constraint in practice.

$x_{\text{e}}, y_{\text{e}}$	Saprang was considered one of the top contenders to lead the army and the junta after CNS leader Sonthi Boonyaratkalin's mandatory retirement in 2007. However, in September 2007 he was demoted to be Deputy Permanent Secretary of the Defense Ministry, while his rival, General Anupong Paochinda, was promoted **to Deputy Attorney General. Later, he was replaced**
x_{loc}	In 1663 Scottish mathematician James Gregory had suggested in his Optica Promota that observations of a transit of the planet Mercury, at widely spaced points on the surface of the Earth, could be used to calculate the solar parallax and hence the astronomical unit using triangulation. Aware of this, a young Edmond Halley made observations of such a transit on 28 October O.S. 1677 from Saint Helena but was disappointed to find that only Richard Towneley in Burnley, Lancashire had made another accurate observation of the event whilst Gallet, at Avignon, simply recorded that it had occurred. Halley was not satisfied that the resulting calculation of the solar parallax at 45 " was accurate.
$x'_{\text{e}}, y'_{\text{e}}$	However, in September 2007 he was demoted to be Deputy Permanent Secretary of the Defense Ministry, while his rival, General Anupong Paochinda, was promoted **to Deputy Attorney General. Later, he was replaced**

Table 8: Training set example from the Wikitext editing dataset. Bolded text corresponds to the edit labels y_{e} and y'_{e}. The locality example x_{loc} is used to constrain the pre- and post-edit model's predictive distributions to be similar at for *every* token in the sequence.

B.3 Environment Details

All runs are trained entirely on a single NVIDIA RTX Titan or A40 GPU. No gradient checkpointing or memory-reduction optimizations are used, although bfloat16 is used to fit the largest T5 model onto our GPU. In full precision, the parameters alone of the T5-11B model use all of the memory of our largest GPU. VRAM consumption for training MEND and KE on T5-11B (Figs. 3 and 4) is estimated by doubling the bfloat16 VRAM usage (Wang and Kanwar, 2019). While doubling half precision enabled estimating the memory consumption of ENN, we were unable to train ENN in half precision without numerical instability. All models are based on Huggingface Transformers implementations (Wolf et al., 2019) with some modifications in line with Cao et al. (2021). We use PyTorch (Paszke et al., 2019) for all experiments, specifically using the Higher library (Grefenstette et al., 2019) in order to implement the bi-level optimization in ENN as well as the inner loop of model editing for all algorithms.

C Dataset Construction & Examples

Datasets are constructed to provide pairs of edit input x_{e} and plausible edit label y_{e}. The edit label is not necessarily the 'correct' label; the goal is to provide realistic instances of the *types* of data we would expect to see during test. For example, our dataset might have a sample such as x_{e} = *Where was Ursula K. Le Guin born?* and y_{e} = *Addis Ababa, Oromia, Ethiopia*, even though Ursula K. Le Guin was born in Berkeley, California, USA. However, this fictitious example is still a useful assessment of our model's ability to perform the general type of edit of 'change a person's birthplace'. For the zsRE question-answering dataset Cao et al. (2021) generate fictitious y_{e} in this manner using the top predictions of a BART model fine-tuned on the task of question answering followed by manual human filtering. In practice, this produces alternate edit labels that are plausible and whose types match with the original label. For FEVER fact-checking, there are only two choices for labels, and we sample edit targets 1 and 0 with equal probability. For Wikitext generation, we use a distilGPT-2 model to generate plausible 10-token continuations for a given Wikitext prefix, with the similar motivation to zsRE of providing edit targets that share the structure of the types of edits that we will apply in practice, even if they are not always factual. When qualitatively assessing MEND to correct real errors of the base model using the factual labels, we find that MEND performs reliably, indicating that these label generators provide reasonable proxies for 'real' model edits.