
Stabilizing Equilibrium Models by Jacobian Regularization

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Abstract

Deep equilibrium networks (DEQs) are a new class of models that eschews traditional depth in favor of finding the fixed point of a single non-linear layer. These models have been shown to achieve performance competitive with the state-of-the-art deep networks while using significantly less memory. Yet they are also slower, brittle to architectural choices, and introduce potential instability to the model. In this paper, we propose a regularization scheme for DEQ models that explicitly regularizes the Jacobian of the fixed-point update equations to stabilize the learning of equilibrium models. We show that this regularization adds only minimal computational cost, significantly stabilizes the fixed-point convergence in both forward and backward passes, and scales well to high-dimensional, realistic domains (e.g., WikiText-103 language modeling and ImageNet classification). Using this method, we demonstrate, for the first time, an implicit-depth model that runs with approximately the same speed and level of performance as popular conventional deep networks such as ResNet-101, while still maintaining the constant memory footprint and architectural simplicity of DEQs. Code is available [here](#).

1. Introduction

While conventional deep networks like ResNets (He et al., 2016) and Transformers (Vaswani et al., 2017) rely on hierarchical layer stacking, the recently-proposed deep equilibrium networks (DEQs) (Bai et al., 2019) directly model the “infinite-depth” representation of a single layer f_θ by solving for its fixed point (i.e., “equilibrium”) \mathbf{z}^* :

$$\mathbf{z}^* = f_\theta(\mathbf{z}^*; \mathbf{x}),$$

where \mathbf{x} is the original input. Importantly, to train these models, one could directly differentiate through the final

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equilibrium \mathbf{z}^* by the implicit function theorem (Krantz & Parks, 2012), irrespective of the method used to solve for this equilibrium in the forward pass. Therefore, like other implicit-depth architectures such as Neural ODEs (Chen et al., 2018), DEQs have the notable advantages that their forward passes can rely on any black-box root solvers (e.g., Newton, quasi-Newton, simplest forward iterations), and that their training only consumes $O(1)$ memory. With this formulation, prior works have managed to extend the DEQ framework for multiple large-scale applications, such as language modeling (Bai et al., 2019) and large-scale image classification or segmentation (Bai et al., 2020).

However, these models suffer from a few issues. First, despite their memory efficiency, DEQs are also slower than conventional deep networks that achieve the same level of accuracy. Second, the number of iterations required to solve for the equilibrium quickly grows over the course of training, indicating a trend for approaching instability. Third, the DEQ model is sensitive to architectural choices, and sometimes even small modifications could break the model’s stability of convergence. Some recent works have tackled this third issue by exploiting provably convergent layers via monotone operator splitting theories (Winston & Kolter, 2020) and Lipschitz boundedness (Revay et al., 2020). However, these structural solutions rely extensively on specific layer parameterizations, rendering DEQ models unscalable and even more inflexible.

In this paper, we first summarize and provide empirical evidence on all of these downsides of the equilibrium networks that have so far thwarted many from extending DEQs to both broader applications and more architectural variants. To address these issues, we further propose a regularization solution to improve on DEQ models’ stability, efficiency and flexibility. Importantly, while prior DEQs adopted regularization methods directly borrowed from explicit deep networks (e.g., recurrent dropout (Gal & Ghahramani, 2016)), we introduce a simple and theoretically-motivated Jacobian regularization pursuant to DEQ models’ implicitness. We will discuss in detail how this Jacobian regularization relates to the contractivity of DEQ’s forward non-linear system and backward linear system, and is thus able to effectively stabilize not only forward but also backward dynamics of DEQ networks. There are two immediate benefits of the resulting stability in the dynamics. First, solving a DEQ requires far fewer iterations than before, which makes regularized

DEQs significantly faster than their unregularized counterparts. Second, this model class becomes much less brittle to architectural variants that would otherwise break the DEQ.

We validate the proposed regularization by experiments on both toy-scale synthetic tasks and large-scale real datasets across domains: word-level language modeling on WikiText-103 (Merity et al., 2017) and high-resolution image classification on the full ImageNet dataset (Deng et al., 2009). Empirically, our regularized DEQs are generally 2x to 3x faster than prior DEQs, and can be accelerated to be as fast as explicit deep networks (e.g., ResNets and DenseNets). This is the first time that implicit models are accelerated to this level without sacrificing scalability, accuracy, or structural flexibility. With their $O(1)$ memory footprint, this further establishes implicit models as a strong competitor to explicit deep architectures.

2. Background & Related Work

While explicit deep networks hierarchically stack layers to build a computation graph for their forward and backward propagations, implicit models (Amos & Kolter, 2017; Chen et al., 2018; El Ghaoui et al., 2019; Gould et al., 2019; Bai et al., 2019) do not have a prescribed computation graph. Instead these models solve for a non-linear system. One example is the Neural ODE (Chen et al., 2018), which solves an initial-value ODE problem that involves a residual layer. Another example, which is the primary focus of our work, is the deep equilibrium network (DEQ) (Bai et al., 2019), which reduces the forward pass to a root-solving problem. In this section, we introduce the basics of DEQ models and the relevant threads of work, followed by a discussion of prior approaches to regularizing implicit models.

2.1. Deep Equilibrium Models

Given a layer/block f_θ (which may contain a few shallow sublayers) and an input \mathbf{x} , a deep equilibrium model aims to approximate an “infinite-level” layer stacking of the form $\mathbf{z}^{[i+1]} = f_\theta(\mathbf{z}^{[i]}; \mathbf{x})$ (where $i = 1, \dots, L$, with $L \rightarrow \infty$) by directly solving for its fixed-point representation:

$$\mathbf{z}^* = f_\theta(\mathbf{z}^*; \mathbf{x}).$$

One of the appealing properties of this fixed-point formulation is that one can implicitly differentiate through the equilibrium feature, without dependency on any intermediate activations in the forward pass. Formally, given a loss ℓ , one can directly compute the gradient using the final output:

$$\frac{\partial \ell}{\partial (\cdot)} = \frac{\partial \ell}{\partial \mathbf{z}^*} (I - J_{f_\theta}(\mathbf{z}^*))^{-1} \frac{\partial f_\theta(\mathbf{z}^*; \mathbf{x})}{\partial (\cdot)},$$

where $J_{f_\theta}(\mathbf{z}^*)$ is the Jacobian matrix at equilibrium \mathbf{z}^* .

To solve for the equilibrium, Bai et al. (2019) proposed to use Broyden’s method (Broyden, 1965) to find the root of

$f_\theta(\mathbf{z}^*; \mathbf{x}) - \mathbf{z}^* = 0$; later works (Winston & Kolter, 2020; Revay et al., 2020) and a recent tutorial (Duvenaud et al., 2020) have applied other algorithms, such as Peaceman-Rachford splitting (Peaceman & Rachford, 1955) and Anderson acceleration (Anderson, 1965).

Compared to Neural ODEs, deep equilibrium networks have been demonstrated to scale well to large and high-dimensional tasks, such as language modeling, ImageNet classification, and semantic segmentation (Bai et al., 2019; 2020), and are thus more applicable to domains where deep learning has been traditionally successful. However, unlike ODE flows, DEQ networks do not have a unique trajectory, and are not guaranteed to converge. Thus recent works have also begun to examine the stability and other theoretical properties of DEQs. Winston & Kolter (2020) propose a monotone DEQ that has a unique fixed point. Pabbaraju et al. (2021); Revay et al. (2020) further study the Lipschitz boundedness of monotone DEQs. Kawaguchi (2021) analyze the gradient dynamics of a linearized version of DEQs. Lu et al. (2021) apply an invertible equilibrium model to generative modeling via normalizing flows.

2.2. Regularizing Implicit Models

Just like explicit deep networks, implicit networks can overfit to the dataset; but additionally, they can also become unstable. For instance, Neural ODEs are essentially modeling infinitesimal steps of a residual block (He et al., 2016; Chang et al., 2018), and Grathwohl et al. (2019) found that weight decay & spectral normalization (Miyato et al., 2018) are useful (though expensive) in reducing the rapidly growing number of functional evaluations (NFEs) needed to solve for the ODE endpoint. On the other hand, large-scale DEQ networks (Bai et al., 2019; 2020) have adopted weight normalization (Salimans & Kingma, 2016), recurrent dropout (Gal & Ghahramani, 2016), and group normalization (Wu & He, 2018) for preventing overfitting and divergence. Nonetheless, all these methods are borrowed from explicit deep networks, where they have long been known to work well. They do not exploit the implicitness of implicit models.

More recently, a few different regularization methods have been introduced to specifically fix the numerous issues of the vanilla Neural ODE and continuous normalizing flow models, such as augmenting the hidden state (Dupont et al., 2019), using hyper ODE solvers (Poli et al., 2020), and regularizing higher-order time derivatives (Kelly et al., 2020). These methods directly leverage the dynamical system view of Neural ODEs. However, due to the inherent challenge of solving high-dimensional ODEs, these accelerated Neural ODE models can still easily take > 100 forward iterations even on MNIST classification (Kelly et al., 2020), and even more for their backward pass. In comparison, DEQs scale better to high-dimensional tasks (e.g., 25-30 iterations on

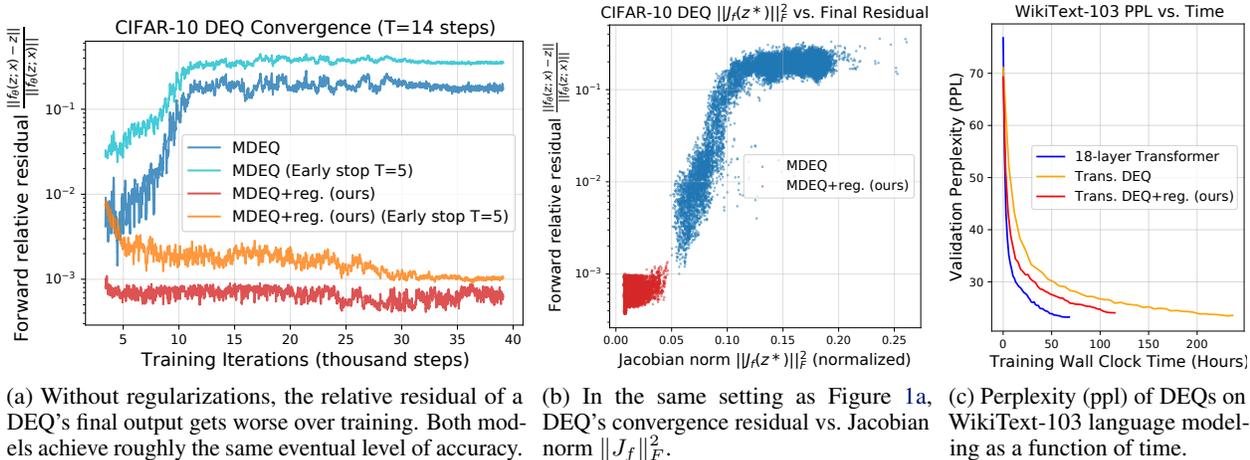


Figure 1. Visualizations of DEQs’ instability and inefficiency problems.

ImageNet (Bai et al., 2020) and complex f_θ (e.g., a Transformer layer). But such extra complexities also make DEQ models harder to regularize; e.g., simply resorting to weight decay doesn’t fix the instability of DEQs (see Section 5.5). To the best of our knowledge, there has been almost no exploration of directly regularizing DEQ stability and convergence.

Our method is closely connected to the many prior works that study Jacobian/gradient regularization (Drucker & Le Cun, 1992; Novak et al., 2018; Hoffman et al., 2019; Finlay et al., 2020; Linsley et al., 2020), though these were also motivated differently. Specifically, Sokolić et al. (2017); Hoffman et al. (2019) regularized the input-output Jacobians of the entire (very deep) explicit classification networks to increase the prediction margin in a robust learning setting (and are thus expensive). Finlay et al. (2020) was inspired by a kinetic energy view and possible overfitting of a training-time dynamical system. The method of Linsley et al. (2020) targeted (for a Jacobian J) a Lipschitzness level λ , used $\max_i (1^\top J)_i$ to approximate the matrix 1-norm, and proposed loss $L = \| (1^\top J - \lambda)^+ \|_2$. Yet this approximation is in fact problematic, as it does not provably bound the spectral radius (i.e., stability) at all. For example, matrix

$$J = \begin{bmatrix} 2 & -2 \\ -2 & 2 \end{bmatrix}$$

has $L = 0$ and yet an eigenvalue of 4 (we also empirically verify that this method does not help DEQ models, exactly due to this issue).

In contrast to these works, the key contributions of our paper are that (1) we provide a thorough discussion & summary of various issues with DEQ models, and how ill-conditioned Jacobians are related to the forward/backward instabilities, via the new lens of fixed-point convergence; and (2) we demonstrate how regularizing the Jacobian of DEQs at the equilibrium point (i.e., the final output z^*) can provably bound the stability of the forward and backward conver-

gences, thereby addressing these various problems. For example, our experiments show that we can significantly stabilize DEQs with new (and more unstable) architectural variants and accelerate DEQs to be nearly as fast as certain explicit architectures (e.g., we only need ≤ 6 NFEs on CIFAR-10) on tasks across different scales and with comparable accuracy.

3. DEQ Models and Their Discontents

Despite the DEQ models’ success in some very challenging tasks, such as Cityscapes semantic segmentation (Cordts et al., 2016; Bai et al., 2020), these models suffer from multiple serious downsides. In this section, we provide a summary of some of these problems. While these issues directly lead to our subsequent discussion on the need for regularization (see Section 4), we also believe such systematic discussion provides a useful overview for potential future research on further addressing these issues.

3.1. Growing Instability during Training

Although a DEQ network has no “depth”, a relevant measure of computational efficiency is the number of function evaluations (NFEs) of the layer $f_\theta(z; x)$ used by the iterative root solver (e.g., Broyden’s method (Broyden, 1965)).

However, one common phenomenon to all prior works on DEQs is that the fixed points are increasingly harder to solve for over the course of model training. In other words, as a DEQ’s performance gradually improves during training, the NFE required to converge to the same threshold ϵ (e.g., 10^{-3}) rapidly grows. This observation has been made on different instantiations of equilibrium networks, and regardless of whether the model is provably convergent or not (e.g., (Bai et al., 2019; Winston & Kolter, 2020), where a DEQ at the end of training can take $> 3\times$ more iterations). Intuitively, such tendency to approach “critical stability” implicitly characterizes an inclination of the model to learn

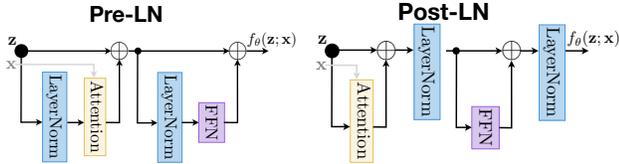


Figure 2. Pre- vs. post-LN DEQ-Transformer layer (Xiong et al., 2020). FFN is a 2-layer feed-forward block (Vaswani et al., 2017).

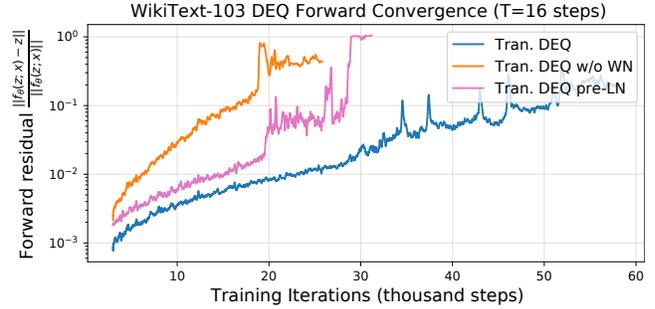
“deeper” networks; so it is unsurprising that unregularized training will keep driving it in this direction. But as a result, the dynamical system only becomes more and more brittle. The existing way of “addressing” this is to circumvent it by setting a maximum NFE limit besides the ε -threshold; i.e., the solver stops either when 1) the residual is smaller than ε , or 2) it has run for a max number of steps T . This could be risky because as the convergence gets more unstable/critical, such a hard stop for the solver cannot guarantee that we are close enough to the fixed point. In the backward pass, for instance, we may consequently be training DEQs with very noisy gradients. A similar issue exists for Neural ODEs, though these cannot easily be hard-stopped like DEQs due to the need to accurately trace the flow to the endpoint.

We illustrate this issue on CIFAR-10 classification in Fig. 1a. One can easily see that both forward and backward estimates of the fixed points gets increasingly worse with the training steps (and eventually plateaus in an unstable region where the model keeps yielding bad gradients). Such growing instability is also reflected empirically in the growth of Jacobian norm at equilibrium; i.e., $\left\| \frac{\partial f_\theta(\mathbf{z}^*; \mathbf{x})}{\partial \mathbf{z}^*} \right\|_F$ (see Figure 1b), which we discuss in Section 4. Moreover, interestingly, while these plots might suggest simple regularizations like weight decay, we show later that weight decay often makes this stability issue worse for equilibrium networks, and even leads to divergence.

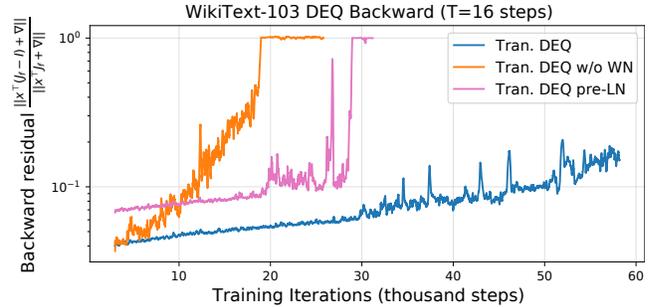
3.2. Inefficiency Compared to Explicit Networks

A direct ramification of the increase in iterations required (see Section 3.1) is the significant increase in both training and inference time for DEQ models.

One advantage of DEQs noted by Bai et al. (2019) is that the forward trajectory need not strictly reach the equilibrium. Therefore in a certain sense, we could trade performance for efficiency by stopping at a “good enough” estimate of the equilibrium. However, due to the growing instability problem, this could still be increasingly costly. This causes the existing DEQs to be significantly slower than their explicit network counterparts of comparable size and performance. E.g., a DEQ-Transformer (Bai et al., 2019) is about $3\times$ slower than a deep Transformer-XL (Dai et al., 2019); a multiscale DEQ (Bai et al., 2020) is over $4\times$ slower than ResNet-101 on ImageNet. Despite their memory efficiency, such slowdown is a roadblock to wider deployment of this



(a) Forward final objective of fixed-point convergence



(b) Backward final objective of fixed-point convergence

Figure 3. Comparing different architectural modifications of a DEQ-Transformer (first 60K steps). The DEQ networks are brittle: even slight modifications such as changing the whereabouts of LayerNorm (see Figure 2) or removing weight normalization can cause the model to quickly diverge during training.

class of models in practice. In Figure 1c, we visualize this slowdown on the validation set of WikiText-103 language modeling (Merity et al., 2017) (with comparable model sizes and number of training steps).

3.3. Brittleness to Architectural Choices

The need to have a relatively stable DEQ in order to train it via the implicit function theorem also calls for more careful attention in designing the layer f_θ . For example, the largest-scale DEQs (Bai et al., 2019; 2020) all had normalizations (Ba et al., 2016; Wu & He, 2018) at the end of the layer to constrain the output range. How important are these architectural choices? We demonstrate the brittleness of DEQs by ablative studies on the use of layer normalization (LN) or weight normalization (WN) in the DEQ-Transformer model on the large-scale WikiText-103 language modeling task. Specifically, we compare the use of the two most popular Transformer layer designs in the DEQ framework: *pre-LN* and *post-LN*, which simply inserts the LN layers at different parts of the block (see Figure 2). These two settings have been extensively studied, used, and compared in the literature (Liu et al., 2020; Xiong et al., 2020; Vaswani et al., 2017; Baevski & Auli, 2019; Dosovitskiy et al., 2020).

The result is shown in Figure 3. Without layer normaliza-

tion at the end (magenta line), the DEQ quickly diverges after 25K training iterations (reflected in both forward and backward divergences). Similarly, without weight normalization (orange line), the model becomes unstable more quickly, with fixed-point solver collapse at around 18K iterations. The original DEQ-Transformer (Bai et al., 2019) (blue line in Figure 3), although not diverged, still suffers from the same increased instability problem as described in Section 3.1. These plots are strong indicators that while equilibrium networks work on large scales, they are also relatively inflexible, brittle, and reliant on meticulous architectural designs.

3.4. The Hidden Cost of the Choice of Solver

Although DEQ models enjoy constant memory consumption during training time and can use any black-box fixed point solvers in the forward and backward passes, a commonly neglected cost is that introduced by the choice of solver. For example, in Broyden’s method (Broyden, 1965) which Bai et al. (2019; 2020) used, the inverse Jacobian J^{-1} is approximated by low-rank updates of the form $J^{-1} \approx -I + \sum_{i=1}^n \mathbf{u}^{[i]} \mathbf{v}^{[i]\top} = -I + UV^\top$. As another example, Anderson mixing (Anderson, 1965) stores and uses the past m iterations ($\mathbf{z}^{[n-1]}, \dots, \mathbf{z}^{[n-m]}$). In most such cases, even storing these updates or past steps can be expensive. Moreover, since we depend on the same DEQ solvers also at inference time, we need to spend this same memory cost even when the trained model is served – which conventional deep networks can avoid. We note that this cost depends strongly on the solver; for example, the simplest iterative “solver” $\mathbf{z}^{[i+1]} = f_\theta(\mathbf{z}^{[i]}; \mathbf{x})$ wouldn’t have any memory cost, but suffers from bad convergence. This issue also highlights the value of faster and stabler convergence, which entails less memory storage overall (e.g., fewer Broyden steps).

4. Regularizing the Jacobian of DEQs

We hypothesize that one of the fundamental factors contributing to some of the problems discussed in Section 3 is that DEQ models’ conditioning is not properly regularized during training. Such trend for DEQ models to go unstable is reflected in Figures 1a and 1b, where increasing training steps leads to monotonically growing residual difference and the Jacobian norm at the equilibrium. We now describe how the Jacobian is related to the stability of equilibrium networks’ forward and backward passes, and then harness this relationship to stabilize and accelerate DEQs.

4.1. The DEQ Jacobian

We first recall that the forward pass of a DEQ network aims to solve for the fixed-point representation \mathbf{z}^* of a layer $f_\theta(\cdot; \mathbf{x})$; i.e., $\mathbf{z}^* = f_\theta(\mathbf{z}^*)$. Then in the backward pass, one

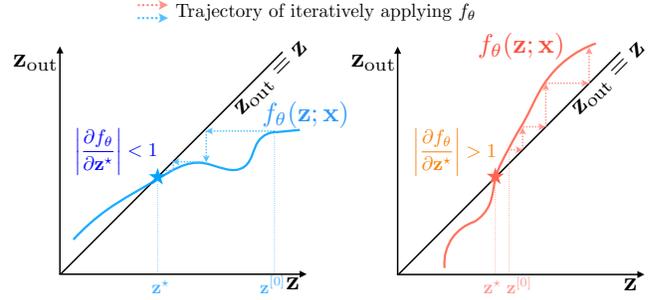


Figure 4. Left: when the slope is less than 1, even the simplest iterative application of f_θ converges. Right: when slope > 1 , the iterative approach may diverge or oscillate, but the fixed point still exists and can be solved for.

can differentiate directly through the equilibrium \mathbf{z}^* by

$$\frac{\partial \ell}{\partial (\cdot)} = \frac{\partial \ell}{\partial \mathbf{z}^*} \underbrace{(I - J_{f_\theta}(\mathbf{z}^*))^{-1}}_{\mathbf{u}^\top} \frac{\partial f_\theta(\mathbf{z}^*; \mathbf{x})}{\partial (\cdot)}. \quad (1)$$

However, because the scale of J_{f_θ} can be prohibitively large and the inverse is costly to compute, we usually compute the \mathbf{u}^\top term in Eq. 1 by solving the following linear fixed-point system that depends on the final Jacobian:

$$\mathbf{u}^\top = \mathbf{u}^\top J_{f_\theta}(\mathbf{z}^*) + \frac{\partial \ell}{\partial \mathbf{z}^*}. \quad (2)$$

Consider the spectral radius of the Jacobian $J_{f_\theta} \in \mathbb{R}^{d \times d}$ at the equilibrium:

$$\rho(J_{f_\theta}(\mathbf{z}^*)) = \rho(J_{f_\theta}(\mathbf{z}^*)^\top) = \max(|\lambda_1|, \dots, |\lambda_d|),$$

where λ_i s are eigenvalues. In both the forward and backward passes, this spectral radius directly affects how stable the convergence to the fixed point \mathbf{z}^* could be in its neighborhood. For instance, in the extreme case where we have a contractive $\rho(J_{f_\theta}) < 1$, by Lyapunov linearization theorem even the simplest iterative calls to $f_\theta(\mathbf{z})$ (in forward, assuming good initial estimate) or $g(\mathbf{u}) = \mathbf{u}^\top J_{f_\theta}(\mathbf{z}^*) + \frac{\partial \ell}{\partial \mathbf{z}^*}$ (in backward) could converge uniquely, even without advanced solvers. The linear system (2), in particular, would enjoy global asymptotic stability. However in practice, we don’t always, and probably shouldn’t, require such a strong contractivity on the dynamical system, which might significantly limit the representational capacity of the model. For example, as shown in Figure 4, a fixed point can exist even if $\rho(J_{f_\theta}) > 1$, (the curve slope in 2D); and we are still able to solve for them using the much stronger root solvers (e.g., Newton or quasi-Newton) than these simplest iterative stackings, which could oscillate or diverge.

4.2. Jacobian Regularization

These connections between $J_{f_\theta}(\mathbf{z}^*)$ (which characterizes the shape of the transformation f_θ around \mathbf{z}^*) and the for-

ward/backward pass dynamics of DEQs motivate us to append a soft and auxiliary Jacobian term $\rho(J_{f_\theta}(\mathbf{z}^*))$ to the training objective in order to regularize the model’s conditioning. One way of doing this is by spectral normalization, essentially constraining $\sigma(J_{f_\theta}) = \max_{\|\mathbf{v}\| \leq 1} \|J_{f_\theta} \mathbf{v}\|_2$. However, explicitly writing out the huge Jacobian and then decomposing it (e.g., by SVD) can be computationally prohibitive, and Miyato et al. (2018) proposes to use the power method (von Mises & Pollaczek-Geiringer, 1929) to speed up this estimation on GANs. But in the context of DEQs, even power iterations are too expensive due to the successive vector-Jacobian product computations needed. Instead, we propose to regularize the Jacobian through its Frobenius norm since

$$\rho(J_{f_\theta}) \leq \sigma(J_{f_\theta}) \leq \sqrt{\text{tr}(J_{f_\theta} J_{f_\theta}^\top)} = \|J_{f_\theta}\|_F.$$

Importantly, $\|J_{f_\theta}\|_F$ can be approximated via various unbiased estimators (Hutchinson, 1989; Ubaru et al., 2017; Meyer et al., 2021). We adopt the classical Hutchinson estimator (Hutchinson, 1989); formally, for $J_{f_\theta} \in \mathbb{R}^{d \times d}$,

$$\text{tr}(J_{f_\theta} J_{f_\theta}^\top) = \mathbb{E}_{\epsilon \in \mathcal{N}(0, I_d)} [\|\epsilon^\top J_{f_\theta}\|_2^2], \quad (3)$$

which we can approximate by Monte-Carlo estimation (i.e., sampling M i.i.d. $\epsilon_i \in \mathcal{N}(0, I_d)$). Specifically, prior works (Avron & Toledo, 2011; Roosta-Khorasani & Ascher, 2015) have established that the relative error of this estimation diminishes with $M^{-\frac{1}{2}}$; and if we compute the mean estimation over a mini-batch size B , the overall relative error with respect to $\mathbb{E}_{\mathbf{x} \sim p(\mathbf{x}), \epsilon \in \mathcal{N}(0, I_d)} [\|\epsilon^\top J_{f_\theta}\|_2^2]$ is expected to further diminished by a factor of $B^{-\frac{1}{2}}$ (Hoffman et al., 2019).

Indeed, empirically, we find that $M = 1$ already works well since we use relatively large batch sizes. Since our backward iterations already involved computing multiple vector-Jacobian products $\mathbf{u}^\top J_{f_\theta}$ (see Eq. (2)), computing Eq. (3) only adds a cost equivalent to that of $M = 1$ backward steps. The eventual training objective is thus

$$\mathcal{L}_{\text{total}}(\mathbf{z}^*) = \mathcal{L}_{\text{orig}}(\mathbf{z}^*) + \gamma \frac{\|\epsilon^\top J_{f_\theta}(\mathbf{z}^*)\|_2^2}{d}, \quad \epsilon \in \mathcal{N}(0, I_d) \quad (4)$$

As we observed in Figure 1a, without regularization, a DEQ model that stops after a fixed number T of solver iterations exhibits increasingly poor convergence, accompanied by a growing $\|J_{f_\theta}\|_F$ at these fixed points that empirically signals the growing instability. Therefore, by constraining the Jacobian’s Frobenius norm, we encourage DEQs to optimize for stabler and simpler dynamics whose fixed points are easier to solve for.

4.3. Memory Considerations

Although the loss objective (4) only adds minimal computation cost, the need to backpropagate through $\|\epsilon^\top J_{f_\theta}\|_2^2$ means we also spend more memory during training to store the

computation graph of this vector-Jacobian product. But at the same time, our hidden memory cost due to the solver choice is smaller (e.g., Broyden’s method; see Section 3.4) as we can lower the number of iterations. As a result, empirically we notice a roughly 30% net growth in memory consumption compared to the unregularized DEQs at training (and thus saving about 50% memory compared to explicit deep networks). The regularized DEQ still consumes $O(1)$ memory relative to the “depth” of the model, as the backpropagation depends only on \mathbf{z}^* .

5. Experiments

We validate the proposed regularization of DEQ models on multiple fronts. First, we visualize the effect of the proposed Jacobian regularization on a tiny DEQ trained on a synthetic 1D dataset. Second, importantly, we focus on how our method alleviates some of the core problems with DEQs outlined in Section 3. Then we show that our method scales to challenging high-dimensional tasks: word-level language modeling with the WikiText-103 dataset (Merity et al., 2017) and image classification with CIFAR-10 and ImageNet (Deng et al., 2009). We specifically compare our model with both prior DEQ networks and competitive explicit models (e.g., ResNet-101, Transformers), in terms of both efficiency (in space and time) and performance. We also explore how Jacobian regularization helps stabilize DEQs over a wider range of architectural choices. Lastly, we perform some ablative studies.

The set of tasks used in our experiment is built directly on top of Bai et al. (2019; 2020). As we found the Jacobian regularization could sometimes hurt performance (see Sec. 5.3), we only apply the proposed loss stochastically with a probability p , and gradually increase this p or the regularization strength γ (see Eq. (4)) over training steps. We also use cosine learning rate schedule (Loshchilov & Hutter, 2017) for all tasks, including the synthetic one. The memory and speeds reported are benchmarked across different models on the same setting (e.g., same batch size, sequence length, number of steps, etc.) with the same GPU. We provide more details regarding the tasks, hyperparameters, datasets, and hardware in Appendix A, and extra experimental results in Appendix B. Our code and pretrained models are provided [here](#).

5.1. Visualization with Synthetic Data

We start by empirically verifying the validity of the approach and visualizing its effect on a synthetic dataset. We generated 5096 scalar data pairs (x, y) using function $y = h(x) = \frac{3}{2}x^3 + x^2 - 5x + 2 \sin(x) - 3 + \delta$ (where $\delta \in \mathcal{N}(0, 0.05)$), and split them into 4096 and 1000 training and validation samples, respectively. We then train a tiny

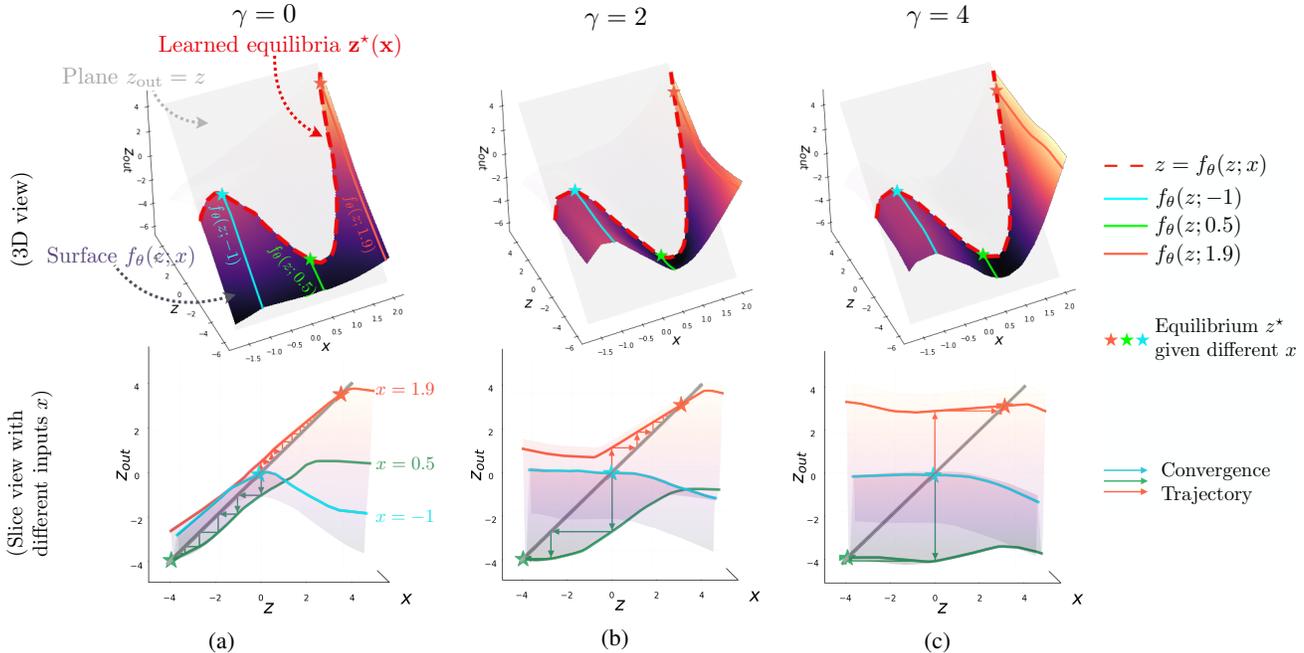


Figure 5. Top: the surface of the $f_\theta(\mathbf{z}; \mathbf{x})$ layer, and the eventual learned equilibria $z^*(x)$ as a function of x . As γ grows, the surface is “lifted up” and becomes flat in the z -direction. **Bottom:** each unique input x defines a slice of the surface, and we perform fixed-point solving on this slice; larger γ values flatten the curve and significantly accelerate the convergence to equilibrium.

DEQ with 200 parameters with the following structure:

$$f_\theta(\mathbf{z}; \mathbf{x}) = W_2^\top \text{ReLU}(W_1 \mathbf{z} + U \mathbf{x} + b), \quad \hat{y} = \mathbf{z}^*$$

where we used $\mathbf{z}, \mathbf{x} \in \mathbb{R}$ and $W_1, W_2, U \in \mathbb{R}^{50 \times 1}$. The visualizations of the effect of the Jacobian regularization, with different weights γ , are shown in Figure 5. In particular, each input x defines a slice (i.e., cross-section) of the 3D surface $z_{\text{out}} = f_\theta(z; x)$; for example, layer $f_\theta(z; x)$ when input $x = -1$ is highlighted in blue. After training, all three settings successfully learned the (almost) identical equilibrium function $z^*(x)$ (highlighted by the red dashed line) that perfectly fits the target function $h(x)$; but note that surfaces of f_θ with $\gamma = 2, 4$ are “lifted up” significantly compared to the unregularized ($\gamma = 0$) DEQ, which has a steep slope (i.e., large spectral radius in 2D). This slope slows down the fixed-point convergence, as reflected by the zigzag patterns in lower Figure 5a. In contrast, the convergences for the $\gamma > 0$ cases are much faster, and larger γ typically yields flatter surfaces around the equilibrium point.

5.2. WikiText-103 Language Modeling

One of the very first successes of large-scale DEQs was its Transformer instantiation (Bai et al., 2019), which uses a multi-head self-attention (Vaswani et al., 2017) layer as the underlying $f_\theta(\mathbf{z}; \mathbf{x})$ function. Although a DEQ-Transformer is able to perform competitively with a deep Transformer-XL (Dai et al., 2019) in terms of test perplexity, and consumes 60-70% less memory, it is also much slower (about $3\times$; see Figure 1c) and borders on instability. In Table 1, we demonstrate how the Jacobian regularization alleviates this.

Table 1. Evaluation on WikiText-103. PPL stands for Perplexity. All Transformer models are trained for 250K steps. t_{train} stands for relative training time. **JR** stands for Jacobian regularization. NFEs are measured at inference time. \dagger indicates unregularized model hard-stopped at inference time.

	Size	PPL	NFEs	t_{train}
AWD-QRNN (Bradbury et al., 2017)	159M	33.0	-	-
Rel. Memory Core (Santoro et al., 2018)	195M	31.6	-	-
18L-Transformer-XL (Dai et al., 2019)	110M	24.1	-	$1\times$
DEQ-Trans. (Pre-LN) (Bai et al., 2019)	98M	[div.]	30	$3.1\times$
DEQ-Trans. (Post-LN) (Bai et al., 2019)	98M	24.0	30	$3.1\times$
DEQ-Trans. (Post-LN) <i>early stopped</i> \dagger	98M	29.2	12^\dagger	$3.1\times$
DEQ-Trans. (Pre-LN) + JR (ours)	98M	24.5	14	$1.6\times$
DEQ-Trans. (Post-LN) + JR (ours)	98M	24.9	12	$1.5\times$

Compared to the original DEQ models, there are two major improvements. First, we significantly reduce the NFEs required for DEQ-Transformer models while maintaining competitive accuracy. Using the Transformer-XL as a time benchmark ($1\times$), the speed of a DEQ-Transformer is significantly accelerated: training time goes from $3.1\times$ to $1.5\times$. Second, the regularized DEQ model is more flexible with architectural choices. Whereas a Pre-LN DEQ-Transformer (see Figure 2) quickly diverges in training even in the presence of a large NFE threshold, the Jacobian regularization resolves this issue and stabilizes the forward/backward convergences consistently (see Figure 3 and Table 1), eventually reaching 24.5 perplexity. Moreover, while we can early-stop a well-trained unregularized DEQ model at inference time, it hurts generalization performance significantly (e.g., 29.2 ppl with 12 NFEs). Similarly, we find training with NFEs

Table 2. Results on CIFAR-10 and ImageNet classification. The CIFAR-10 accuracy standard deviation is calculated with 5 runs. **JR** stands for Jacobian regularization. [†] indicates unregularized model hard-stopped at inference time.

CIFAR-10 classification			
	Size	Accuracy	NFEs
ResNet-18 (He et al., 2016)	10M	93.0 (± 0.1)%	-
ResNet-101 (He et al., 2016)	40M	93.8 (± 0.3)%	-
DenseNet-121 (Huang et al., 2017)	8M	95.0 (± 0.1)%	-
monotone DEQ (Winston & Kolter, 2020)	1M	89.4 (± 0.2)%	24
MDEQ (Bai et al., 2020)	10M	93.6 (± 0.2)%	17
MDEQ <i>early stopped</i> [†]	10M	89.1%	6 [†]
MDEQ + JR (ours) (Bai et al., 2020)	10M	93.1 (± 0.3)%	6

(Full) ImageNet classification			
	Size	Top-1 Acc.	NFEs
ResNet-18 (He et al., 2016)	13M	70.2%	-
Inception-V2 (Ioffe & Szegedy, 2015)	12M	74.8%	-
ResNet-50 (He et al., 2016)	26M	75.1%	-
ResNet-101 (He et al., 2016)	52M	77.1%	-
DenseNet-264 (Huang et al., 2017)	74M	79.7%	-
MDEQ-small (Bai et al., 2020)	18M	75.4%	27
MDEQ-large (Bai et al., 2020)	63M	77.5%	30
MDEQ-small + JR (ours)	17M	74.5%	14
MDEQ-large + JR (ours)	62M	76.8%	15

< 30 leads to increasingly bad generalization performance, and when NFEs drops below 20, model training frequently diverge as a result of extremely noisy gradients. We provide more comprehensive results in Table 5 in the Appendix.

Like DEQs, the regularized DEQs are memory efficient, consuming about 45% less training memory than Transformer-XL. Moreover, we find the Jacobian-regularized DEQs reduce over 50% memory consumption of the original DEQs at inference time (when both using Broyden’s method) due to faster/stabler convergence, suggesting its effectiveness in addressing the hidden solver cost issue discussed in Sec. 3.4.

5.3. CIFAR-10 and ImageNet Classification

We additionally conduct experiments on vision tasks using the recent multiscale deep equilibrium networks (MDEQ) (Bai et al., 2020), which drive multiple feature resolutions to their equilibria simultaneously. Because of the need to maintain high- and low-resolutional feature maps at all iterative steps and generally higher channel dimensions in f_θ , MDEQs are substantially slower than conventional networks like ResNets (which operate on progressively down-sampled feature maps). This makes acceleration vital to broader adoption of multiscale implicit models.

The results of applying Jacobian regularization on multiscale DEQs for image classification are shown in Table 2. On CIFAR-10, whereas the unregularized DEQ models used 17 NFEs to reach the reported competitive level of performance, our DEQ with Jacobian regularization can converge well even within 6 iterations (in fact, we find smaller NFE values still trains, but significantly hurts generalization performance). This improvement is also obvious in Figure 1a

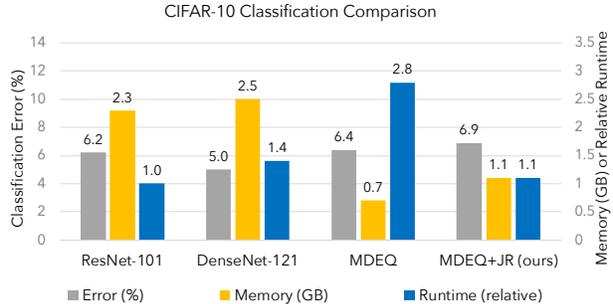


Figure 6. With the proposed regularization, DEQ models are competitive with popular explicit networks in accuracy, memory, and runtime. **Lower bars are better.**

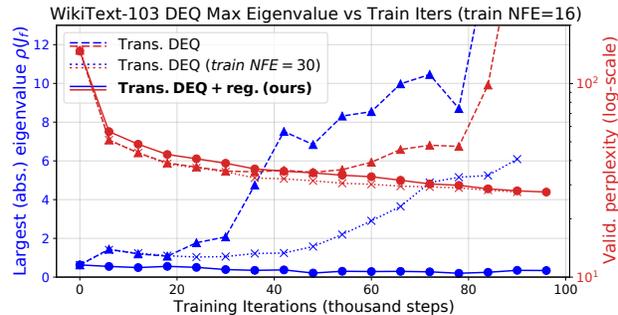


Figure 7. Empirical evidence of how our method constrains $\rho(J_{f_\theta})$. In contrast, insufficient NFEs (e.g., $T=16$) at training time cause a DEQ-Transformer model to explode early in the training phase.

and 1b, where we show that early stopping at threshold $T = 6$ still yields good convergence with Jacobian regularization. We also demonstrate a more stable backward pass convergence throughout training in Appendix B. On the much larger-scale ImageNet, where we deal with 224×224 images, the factor of reduction in NFE is not as strong (e.g., from 27 to 14 iterations, due to the receptive field issue; we’ll explain this in Section 5.5) but still yields a roughly $2\times$ acceleration. This shows that the Jacobian regularization is effective in large-scale computer vision tasks, and in the presence of multiple equilibrium points. However, we also note that as with DEQ-Transformers on WikiText-103, we notice a small slip in accuracy, which may be a result of constraining model parameterizations.

Figure 6 provides a visual comparison of different models with respect to three metrics: performance, inference speed, and training memory. These are reported on the CIFAR-10 dataset. For the first time, we have an implicit-depth model that runs with a competitive level of speed and accuracy as large explicit networks such as ResNet-101, while consuming much less memory.

5.4. Effect of Jacobian Regularization on $\rho(J_{f_\theta})$

In addition to the synthetic study, we also verify that the Jacobian regularization is indeed effectively constraining conditioning of J_{f_θ} . Note that the underlying Jacobian matrices

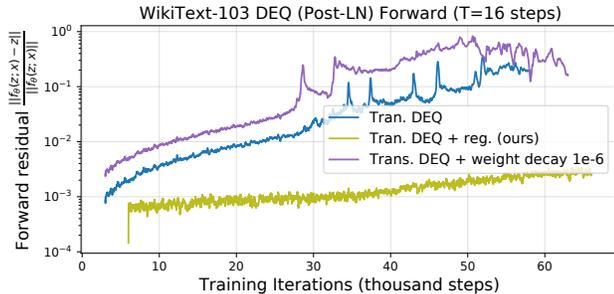


Figure 8. Adding weight decay of magnitude 10^{-6} to the DEQ-Transformer doesn’t help stabilize the forward convergence.

Table 3. Controlled experiments on the strength γ of the Jacobian regularization. The NFE value represents the “hard stop” threshold we set for the corresponding DEQ models at inference.

	NFE=1	NFE=2	NFE=3	NFE=4	NFE=5	NFE=6
$\gamma = 0.1$	82.4%	89.7%	91.9%	92.3%	92.7%	92.9%
$\gamma = 0.6$	85.8%	91.5%	92.7%	93.0%	93.0%	93.1%
$\gamma = 1.2$	84.4%	89.6%	92.2%	92.6%	92.7%	92.7%

are large (e.g., $[(B \cdot 110K) \times (B \cdot 110K)]$ in WikiText-103, and $[(B \cdot 198K) \times (B \cdot 198K)]$ in ImageNet with MDEQ-small) and checking their full spectrum would be infeasible. Therefore, we conduct a study that monitors the average spectral radius $\rho(J_{f_\theta}(z^*))$ (i.e., the largest absolute eigenvalue) on the validation set, over the first 100K steps of DEQ training on WikiText-103 using the power method (von Mises & Pollaczek-Geiringer, 1929); see Fig. 7. Importantly, although $\|J_{f_\theta}\|_F$ only upper-bounds the spectral radius (see Sec. 4.2), we verify that our proposed regularization does effectively constrain $\rho(J_{f_\theta})$ (see ●/● paths in Fig. 7), thereby making DEQs more stable. In contrast, the unregularized DEQ with the same few NFEs explodes in both eigenvalue and shortly after also in perplexity (see ▲/▲ paths), and only works if we increase NFE to 30 (see ×/× paths). In general, we empirically observe that training an unregularized DEQ with insufficient NFEs generally begets extremely noisy gradients, thus leading to faster destabilization and even divergence.

5.5. Ablative Analysis and Limitations of the Approach

We continue our discussion with some empirical ablative studies. First, while Grathwohl et al. (2019) found weight decay useful for regularizing ODE-based models’ NFEs, we found weight decay generally not effective in stabilizing DEQs and sometimes even counter-productive. This is illustrated in Figure 8, where after 50K steps the model started to diverge to > 500 perplexity and stopped improving. In addition, we also conduct an ablative experiment on how the Jacobian regularization strength γ affects the performance when we constrain NFEs to ≤ 6 at inference time, with results shown in Table 3 (CIFAR-10 dataset). In general, we find that if γ is too small, the final performance may be good but entails more NFEs. When γ is too large, the accuracy

does quickly converge, but the constraint imposed on the model class is too strong and eventually hurts performance (e.g., since the training loss on CIFAR-10 usually overfits to almost 0 towards the end of training, which makes the Jacobian loss dominant instead).

We also highlight two limitations of this approach. First, the addition of Jacobian regularization term does not fundamentally solve the growing instability problem, but only empirically alleviates it. This means that we have to be careful about balancing the main loss objective and this auxiliary objective (see Table 3). Second, while Jacobian regularization facilitates faster convergence, there are certain “physical laws” that we simply cannot bypass. For example, if we apply a shallow convolutional DEQ whose layer has receptive field 5×5 on a large image (e.g., 1024×1024), it is hard to be able to reach the fixed point with just 6 iterations simply because the model’s receptive field may not broaden sufficiently to cover valuable context. Although one can possibly still force convergence with a large γ , it would undoubtedly hurt the performance. This explains why we need more NFEs on ImageNet than on CIFAR-10 (see Table 2); it also indicates that while our approach alleviates the brittleness to architectural choices, its effectiveness can still depend on the architecture. This makes global-context alternatives to ConvNets, such as self-attention-based vision layers (e.g., ViT (Dosovitskiy et al., 2020)) likely more appealing in the implicit model setting, which we leave for future work.

6. Conclusion

We summarized the weaknesses of existing DEQ models, including instability & inefficiency, architectural brittleness, and hidden memory costs. We specifically discussed the relationship between the spectral radius of the Jacobian and the stability of forward non-linear and backward linear systems of DEQ models, and provided empirical evidence of the poor conditioning of the Jacobian. This motivates our introduction of Jacobian regularization. Our experiments show that our method significantly alleviates the weaknesses of DEQs, yielding a $> 2.5\times$ acceleration. This is a major step towards making implicit models more practical and suitable for large-scale real-world applications. We hope that our work will motivate further research that advances our understanding and application of this class of models.

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