ESTIMATING LIPSCHITZ CONSTANTS OF MONOTONE DEEP EQUILIBRIUM MODELS

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ABSTRACT

Several methods have been proposed in recent years to provide bounds on the Lipschitz constants of deep networks, which can be used to provide robustness guarantees, generalization bounds, and characterize the smoothness of decision boundaries. However, existing bounds get substantially weaker with increasing depth of the network, which makes it unclear how to apply such bounds to recently proposed models such as the deep equilibrium (DEQ) model, which can be viewed as representing an infinitely-deep network. In this paper, we show that monotone DEQs, a recently-proposed subclass of DEQs, have Lipschitz constants that can be bounded as a simple function of the strong monotonicity parameter of the network. We derive simple-yet-tight bounds on both the input-output mapping and the weight-output mapping defined by these networks, and demonstrate that they are small relative to those for comparable standard DNNs. We show that one can use these bounds to design monotone DEQ models, even with e.g. multi-scale convolutional structure, that still have constraints on the Lipschitz constant. We also highlight how to use these bounds to develop PAC-Bayes generalization bounds that do not depend on any depth of the network, and which avoid the exponential depth-dependence of comparable DNN bounds.

1 INTRODUCTION

Measuring the sensitivity of deep neural networks (DNNs) to changes in their inputs or weights is important in a wide range of applications. A standard way of measuring the sensitivity of a function f is the *Lipschitz constant* of f, the smallest constant $L \in \mathbb{R}_+$ such that $\|f(x)-f(y)\|_2 \leq L\|x-y\|_2$ for all inputs x and y. While exact computation of the Lipschitz constant of DNNs is NP-hard (Virmaux & Scaman, 2018), bounds or estimates can be used to certify a network's robustness to adversarial input perturbations (Weng et al., 2018), encourage robustness during training (Tsuzuku et al., 2018), or as a complexity measure of the DNN (Bartlett et al., 2017), among other applications. An analogous Lipschitz constant that bounds the sensitivity of f to changes in its weights can be used to derive generalization bounds for DNNs (Neyshabur et al., 2018). A growing number of methods for computing bounds on the Lipschitz constant of DNNs have been proposed in recent works, primarily based on semidefinite programs (Fazlyab et al., 2019; Raghunathan et al., 2018) or polynomial programs (Latorre et al., 2019). However, as the depth of the network increases, these bounds become either very loose or prohibitively expensive to compute. Additionally, they are typically not applicable to structured DNNs such as convolutional networks which are common in everyday use.

The deep equilibrium model (DEQ) (Bai et al., 2019) is an *implicit-depth* model which directly solves for the fixed point of an "infinitely-deep", weight-tied network. DEQs have been shown to perform as well as DNNs in domains such as computer vision (Bai et al., 2020) and sequence modelling (Bai et al., 2019), while avoiding the large memory footprint required by DNN training in order to backpropagate through a long computation chain. Given that DEQs represent infinite-depth networks, however, their Lipschitz constants clearly cannot be bounded by existing methods, which are very loose even on networks of depth 10 or less.

In this paper we take up the question of how to bound the Lipschitz constant of DEQs. In particular, we focus on *monotone* DEQs (monDEQ) (Winston & Kolter, 2020), a recently-proposed class of DEQs which parameterizes the DEQ model in a way that guarantees existence of a unique fixed-

point, which can be computed efficiently as the solution to a monotone operator splitting problem. We show that monDEQs, despite representing infinite-depth networks, have Lipschitz constants which can be bounded by a simple function of the strong-monotonicity parameter, the choice of which therefore directly influences the bound. We also derive a bound on the Lipschtiz constant w.r.t. the weights of the monDEQ, with which we derive a deterministic PAC-Bayes generalization bound for the monDEQ by adapting the technique of (Neyshabur et al., 2018). While such generalization bounds for DNNs are plagued by exponential dependence on network depth, the corresponding monDEQ bound does not involve any depth-like term.

Empirically, we demonstrate that our bounds on fully-connected monDEQs trained on MNIST are small relative to comparable DNNs, even for DNNs of depth only 4. We show a similar trend on single- and multi-convolutional monDEQs as compared to the bounds on traditional CNNs computed by AutoLip and SeqLip (Virmaux & Scaman, 2018), the only existing methods for (even approximately) bounding CNN Lipshitz constants. Further, our monDEQ generalization bounds are comparable with bounds on DNNs of around depth 5, and avoid the exponential dependence on depth of those bounds.

2 Background and Related Work

Lipschitz constants of DNNs Lipschitz constants of DNNs were proposed as early as Szegedy et al. (2014) as a potential means of controlling adversarial robustness. The bound proposed in that work was the product of the spectral norms of the layers, which in practice is extremely loose. Virmaux & Scaman (2018) derive a tighter bound via a convex maximization problem; however the bound is typically intractable and can only be approximated. Combettes & Pesquet (2019) bound the Lipschitz constant of DNNs by noting that the common nonlinearities employed as activation functions are averaged, nonexapansive operators; however, their method scales exponentially with depth of the network. (Zou et al., 2019) propose linear-program-based bounds specific to convolutional networks, which in practice are several orders of magnitude larger than than empirical lower bounds. Upper bounds based on semidefinite programs which relax the quadratic constraints imposed by the nonlinearities are studied by Fazlyab et al. (2019); Raghunathan et al. (2018); Jin & Lavaei (2018). The bounds can be tight in practice but expensive to compute for deep networks; as such, Fazlyab et al. (2019) propose a sequence of SDPs which trade off computational complexity and accuracy. This allows us to compare our monDEQ bounds to their SDP bounds for networks of increasing depth (see Section 5). Latorre et al. (2019) show that the complexity of the optimization problems can be reduced by taking advantage of the typical sparsity of connections common to DNNs, but the resulting methods are still prohibitively expensive for deep networks.

DEQs and monotone DEQs An emerging focus of deep learning research is on *implicit-depth* models, typified by Neural ODEs (Chen et al., 2018) and deep equilibrium models (DEQs) (Bai et al., 2019; 2020). Unlike traditional deep networks which compute their output by sequential, layer-wise computation, implicit-depth models simulate "infinite-depth" networks by specifying, and directly solving for, some analytical conditions satisfied by their output. The DEQ model directly solves for for the fixed-point of an infinitely-deep, weight-tied and input-injected network, which would consist of the iteration $z_{i+1} = g(z_i, x)$ where, g represents a nonlinear layer computation which is applied repeatedly, z_i is the activation at "layer" i, and x is the network input, which is injected at each layer. Instead of iteratively applying the function g (which indeed may not converge), the infinite-depth fixed-point $z^* = g(z^*, x)$ can be solved using a root-finding method. A key advantage of DEQs is that backpropagation through the fixed-point can be performed analytically using the implicit function theorem, and DEQ training therefore requires much less memory than DNNs, which need to store the intermediate layer activations for backpropagation.

In standard DEQs, existence of a unique fixed point is not guaranteed, nor is stable convergence to a fixed-point easy to obtain in practice. Monotone DEQs (monDEQs) (Winston & Kolter, 2020) improve upon this aspect by parameterizing the DEQ in a mannr that guarantees the existence of a stable fixed point. Monotone operator theory provides a class of *operator splitting methods* which are guaranteed to converge linearly to the fixed point (see Ryu & Boyd (2016) for a primer). The monDEQ considers a weight-tied, input-injected network with iterations of the form

$$z^{(k+1)} = \sigma(Wz^{(k)} + Ux + b) \tag{1}$$

where $x \in \mathbb{R}^n$ is the input, $U \in \mathbb{R}^{h \times n}$ the input-injection weights, $z^{(i)} \in \mathbb{R}^h$ the hidden unit activations at "layer" i, and $W \in \mathbb{R}^{h \times h}$ the hidden-unit weights, and $b \in R^h$ a bias term, and $\sigma : \mathbb{R}^h \to \mathbb{R}^h$ an elementwise nonlinearity. The output of the monDEQ is defined as the fixed point of the iteration, a z^* such that

$$z^* = \sigma(Wz^* + Ux + b). \tag{2}$$

Just as for DEQs, forward iteration of this system need not converge to z^*; instead, the fixed point is found as the solution to a particular operator splitting problem. Various operator splitting methods can be employed here, for example *forward-backward* iteration, which results in a damped version of the forward iteration

$$z^{(k+1)} = \sigma(z^{(k)} - \alpha((I - W)z^{(k)} - (Ux + b))) = \sigma((I - \alpha(I - W))z^{(k)} + \alpha(Ux + b)). \tag{3}$$

The operator $I - \alpha(I - W)$ appearing in this iteration is *contractive* for any $0 < \alpha \leq 2m/L^2$, and this iteration is guaranteed to converge so long as the operator $I - W$ is Lipschitz and strongly monotone with parameters L (which is in fact the spectral norm $\|I - W\|_2$) and m (Ryu & Boyd, 2016). In Section 3, we will see how unrolling this iteration leads directly to a bound on the Lipschitz constant of the monDEQ. To ensure the strong monotonicity condition, that $I - W \succeq mI$, the monDEQ parameterizes W as

$$W = (1 - m)I - A^T A + B - B^T.$$

The strong-monotonicity parameter m will in fact figure in directly to the Lipschitz constant of the monDEQ.

3 Lipschitz constants for monotone DEQs

We now present our central methodological contributions, easily-computable bounds on the Lipschitz constants of monotone DEQs. We first derive the Lipschitz bound on the input-output mapping defined by the monDEQ, followed by that for the weight-output mapping. As we describe below, both bounds turn out to depend inversely on the strong-monotonicity parameter m of the monDEQ. Since m is chosen for the monDEQ at design time, this implies an analytical handle on its Lipschitz constant.

3.1 Lipschitz constants with respect to input

The naive way of computing L for feedforward deep networks is by multiplying the spectral norms of the weight matrices. As stated above, just employing forward iterations does not lead to convergence of the monDEQ. Analogously, if we were to adopt the naive method and simply unroll the forward iterations of the monDEQ as described in equation 1, we would end up with an infinite product of spectral norms, which would not converge unless W itself is contractive. Here again, we consider unrolling the averaged operator $T := I - \alpha(I - W)$ employed in the forward-backward iterations, which ensures that the monDEQ converges, and will also lead to a finite bound on the Lipschitz constant. Notice that T appears in the forward iterations in equation 3. In the sequel, let $L[A]$ denote the Lipschitz constant of a function or operator A. The following proposition, which we prove in Appendix A, bounds the Lipschitz constant $L[T]$.

Proposition 1. $L[T] \leq \sqrt{1 - 2\alpha m + \alpha^2 L[I - W]^2}$

This implies that for $\alpha \in \left(0, \frac{2m}{L[I-W]^2}\right)$, $L[T] < 1$. In our subsequent analysis, we only consider values of α in this range. We are now ready to state our bound for the Lipschitz constant of the monDEQ:

Theorem 1 (Lipschitz constant of monDEQ)**.** *Let $f(x) = z^*$ denote the output of the monDEQ on input x, as in equation 2. Consider any $x, y \in \mathbb{R}^n$. Then, we have that*

$$\|f(x) - f(y)\|_2 \leq \frac{\|U\|_2}{m} \|x - y\|_2.$$

In other words, $L[f] \leq \frac{\|U\|_2}{m}$.

Proof. Let $f_k(x) = z^{(k)}$ denote the kth iterate of the forward-backward iterations as described in equation 3 (we begin with $f_0(x) = 0$). We will try and unroll these iterations in the following:

$$\begin{aligned}
\|f_k(x) - f_k(y)\|_2 &= \|\sigma(Tf_{k-1}(x) + \alpha Ux + \alpha b) - \sigma(Tf_{k-1}(y) + \alpha Uy + \alpha b)\|_2 \\
&\leq \|Tf_{k-1}(x) + \alpha Ux + \alpha b - Tf_{k-1}(y) - \alpha Uy - \alpha b)\|_2 \quad (\sigma = \text{ReLU is 1-Lipschitz}) \\
&= \|T(f_{k-1}(x) - f_{k-1}(y)) + \alpha U(x-y)\|_2 \leq \|T(f_{k-1}(x) - f_{k-1}(y))\|_2 + \alpha\|U(x-y)\|_2 \\
&\leq L[T]\|f_{k-1}(x) - f_{k-1}(y)\|_2 + \alpha L[U]\|x-y\|_2 \\
&\leq L[T]^k\|f_0(x) - f_0(y)\|_2 + \alpha\|U\|_2\|x-y\|_2 \cdot \sum_{i=0}^{k-1}(L[T])^i \quad (\text{unrolling } k \text{ times}) \\
&= \alpha\|U\|_2\|x-y\|_2 \cdot \sum_{i=0}^{k-1}(L[T])^i \quad (\text{since } f_0(x) = f_0(y) = 0)
\end{aligned}$$

Since the above inequality holds for all k, we can take the limit on both sides as $k \to \infty$, keeping α fixed. But notice that since the forward-backward iterations converge to the true f (which does not depend on α), we have that $\lim_{k\to\infty} f_k = f$. That is, the dependence on α disappears on the LHS once we take the limit on k. Thus,

$$\begin{aligned}
\|f(x) - f(y)\|_2 = \left\|\lim_{k\to\infty} f_k(x) - \lim_{k\to\infty} f_k(y)\right\|_2 &\leq \alpha\|U\|_2\|x-y\|_2 \cdot \sum_{i=0}^{\infty}(L[T])^i \\
&= \frac{\alpha\|U\|_2}{1 - L[T]}\|x-y\|_2 \quad (\text{since } L[T] < 1) \\
&\leq \frac{\alpha\|U\|_2}{1 - \sqrt{1 - 2\alpha m + \alpha^2 L[I-W]^2}}\|x-y\|_2 \quad (\text{from Proposition 1})
\end{aligned}$$

Now, since the above result holds for any α in the range considered, taking $\alpha \to 0$, we have that

$$\begin{aligned}
L[f] &\leq \lim_{\alpha\to 0} \frac{\alpha\|U\|_2}{1 - \sqrt{1 - 2\alpha m + \alpha^2 L[I-W]^2}} \\
&= \frac{\|U\|_2}{m} \quad (\text{applying L'Hopital's rule})
\end{aligned}$$

□

We observe here that the Lipschitz constant of the monDEQ with respect to its inputs indeed depends on only two quantities, namely $\|U\|_2$ and m, and doesn't depend at all on the weight matrix W. Furthermore, because m is a hyperparameter chosen by the user, this illustrates that monDEQs have the notable property that one can directly control the Lipschitz parameter of the network (at least as far as the influence of W is concerned), soley by choosing m, instead of requiring any additionl structure or regularization on W. This is in stark contrast to most existing DNN architectures, where enforcing Lipschitz bounds requires substantial additional effort.

3.2 Lipschitz constants with respect to weights

We now turn to the question of bounding the change in the output of the monDEQ when the *weights* are perturbed but the input remains fixed. This computation has several important use cases, one of which is in the derivation of generalization bounds for the monDEQ. Given a bound on the change in the output on perturbing the weights of the monDEQ, we can derive bounds on the generalization error in a straight-forward manner, as detailed in Section 4 below. In order to derive the perturbation bound, we first state the following proposition (proved in Appendix B), which bounds the norm of the output after k forward-backward iterations.

Proposition 2. *Let $f_k(W, U, b)$ denote the kth iterate of the forward-backward iterations of the monDEQ parameterized by W, U, b on a fixed arbitrary input x. Further, let $T(W) = (1-\alpha)I + \alpha W$. Then, we have that*

$$\|f_k(W, U, b)\|_2 \leq \frac{\alpha\|Ux + b\|_2}{1 - L[T(W)]}$$

We can now derive a perturbation bound for the monDEQ.

Theorem 2 (Perturbation bound for monDEQ)**.** *Let $I - W \succeq mI$ and $I - \bar{W} \succeq \bar{m}I$. The change in the output of the monDEQ on perturbing the weights and biases from W, U, b to $\bar{W}, \bar{U}, \bar{b}$ is bounded as follows:*

$$\|f(\bar{W}, \bar{U}, \bar{b}) - f(W, U, b)\|_2 \leq \frac{\|\bar{W} - W\|_2 \|Ux + b\|_2}{m\bar{m}} + \frac{\|(\bar{U} - U)x\|_2 + \|\bar{b} - b\|_2}{\bar{m}}$$

The proof steps for Theorem 2 parallel closely those involved in the derivation of the Lipschitz constant with respect to the inputs, and are outlined in Appendix C. We highlight here again that the bound depends inversely on m, a design parameter in our control. Further, when compared to a similar perturbation bound derived in Neyshabur et al. (2018), we note that our perturbation bound for the monDEQ *does not* involve a depth-dependent product of spectral norms of weights. Furthermore, although we state the theorem in terms of a perturbation of W (which can thus lead to a different strong monotonicity parameter $\bar{m}$), the bound can also be adapted to perturbations on A and B in the typical monDEQ parameterization, which leads to a perturbed network that will necessarily still have the same monotonicity parameter m as the original (indeed, we take this approach in the next section, when deriving the generalization bound).

4 Generalization bound for monDEQ

In this section, we demonstrate how the perturbation bound derived in Section 3.2 leads directly to a deterministic PAC-Bayes, margin-based bound on the monDEQ generalization error, following the analysis for DNNs of Neyshabur et al. (2018). A key difference from our work, however, is that the perturbation bound they derive involves the product of spectral norms of all the weight matrices in the DNN. Thus, as the network gets deeper, their bound grows exponentially looser. As in Neyshabur et al. (2018), our generalization bound is based on two key ingredients. The first is their deterministic PAC-Bayes margin bound (Lemma 1 in the Appendix D), which adapts traditional PAC-Bayes bounds to bound the the expected risk of a parameterized, deterministic classifier in terms of its empirical margin loss. The second is the perturbation bound on monDEQ with respect to weights as derived in Section 3.2 above. Crucially, since our perturbation bound does not explicitly involve a product of spectral norms of weights (which in the case of the monDEQ, would be an infinite product), our final generalization bound does not either.

The monDEQ model we consider here consists of a fully connected layer at the end that maps f to the output, so that $f_o(x) = W_o f(x) + b_o$, where W_o and b_o are the weights and bias in the output layer; these parameters are important to include here since they contribute directly to the perturbation bound. We also restrict the input x to the monDEQ to lie in an l_2 norm ball of radius B. Let h denote the hidden dimension of the monDEQ, and M the size of the training set, and define $\beta := \max\{\|U\|_2, \|A\|_2, \|b\|_2, \|W_o\|_2\}$. Let $L_\gamma(f_o)$ denote the expected margin loss at margin γ of the monDEQ on the data at the population level, and $\hat{L}_\gamma(f_o)$ denote the corresponding empirical margin loss on the training dataset. We are now ready to state our generalization bound for the monDEQ:

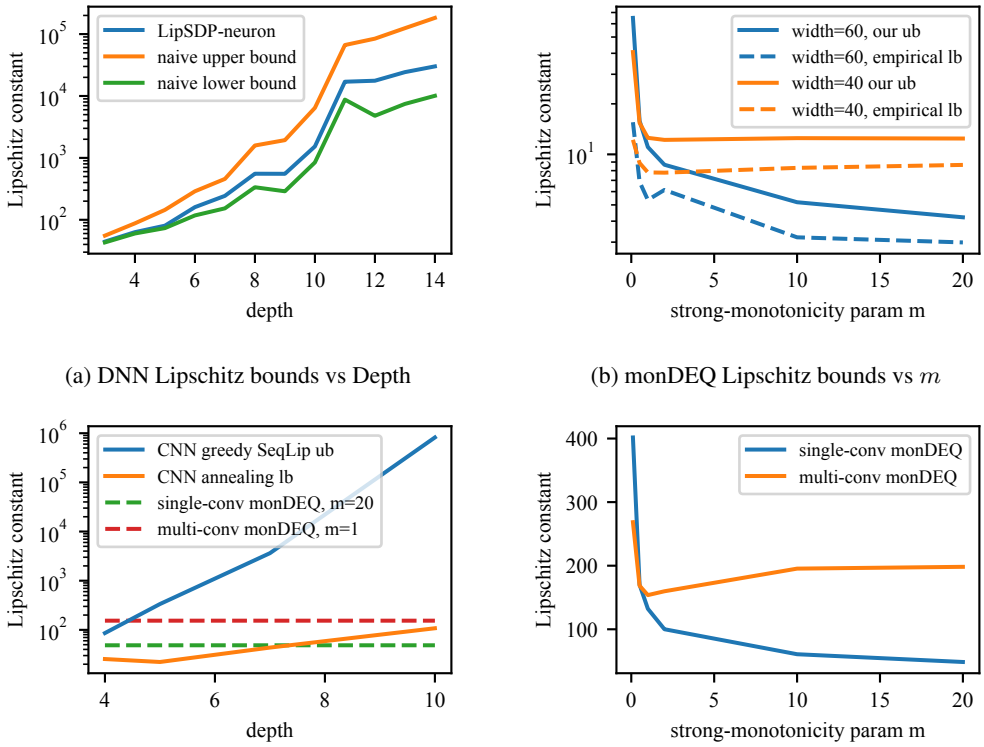
Theorem 3 (Generalization bound for monDEQ)**.** *Let*

$$\sum \|W_\cdot\|_F^2 = \|A\|_F^2 + \|B\|_F^2 + \|U\|_F^2 + \|b\|_F^2 + \|W_o\|_F^2 + \|b_o\|_F^2$$

For any $\delta, \gamma > 0$, with probability at least $1 - \delta$ over the training set of size m, we have that

$$L_0(f_o) \leq \hat{L}_\gamma(f_o) + \mathcal{O}\left(\sqrt{\frac{h \ln(h)[\beta^2 B(\gamma + \beta) + m\beta B + m^2]^2}{\gamma^2 m^4 M} \sum \|W_\cdot\|_F^2 + \frac{\ln(\frac{M\sqrt{M}}{\delta})}{M}}\right)$$

Note that our bound above does not involve any depth-like term that scales exponentially, like the term that involves the product of spectral norms of the weight matrices in Neyshabur et al. (2018). To the best of our knowledge, this is the first generalization bound for an implicit-layer model having effectively infinite depth. The proof of Theorem 3 is given in Appendix D.



(a) DNN Lipschitz bounds vs Depth

(b) monDEQ Lipschitz bounds vs m

(c) CNN bounds vs Depth

(d) Convolutional monDEQ bounds vs m

Figure 1: Lipschitz bounds as a function of depth and strong monotonicity parameter.

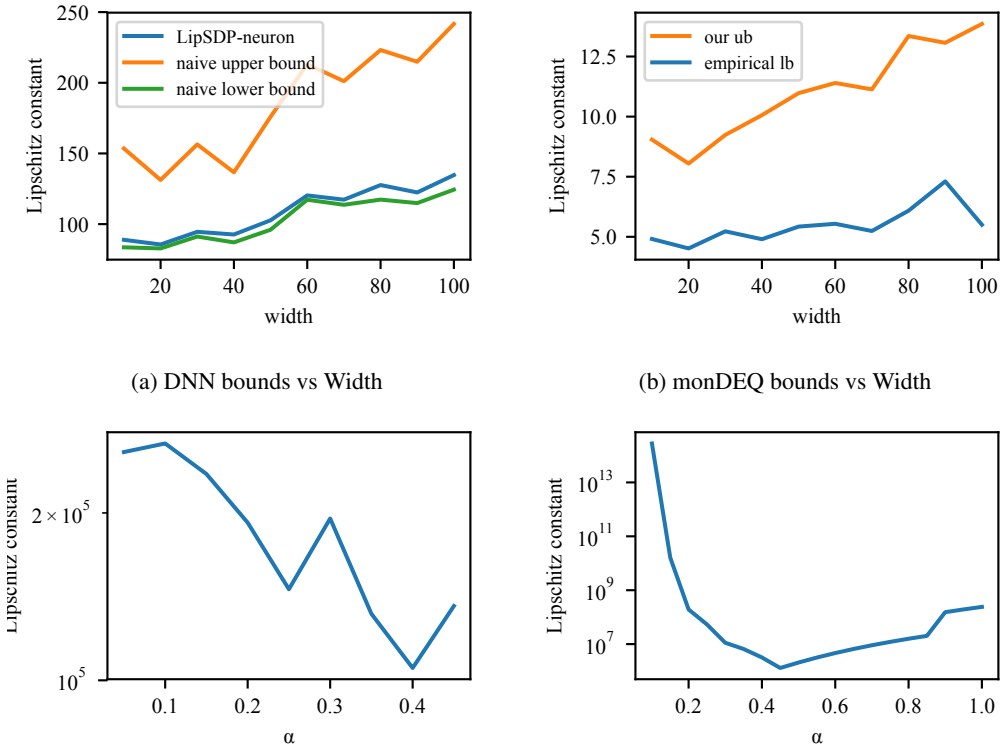
5 Experimental Results

5.1 Lipschitz constants

In this section, we empirically verify the tightness of the Lipschitz constant of the monDEQ with respect to inputs. We conduct all our experiments on the MNIST dataset, for which several benchmarks exist on computing the Lipschitz constant. We conduct a variety of experiments for different monDEQ architectures (fully connected as well as convolutional) with varying parameters (strong-monotonicity parameter m and width h), which we compare to DNNs with different depths and widths. For DNNs with weight matrices $W_1, \ldots, W_d$, we also compute an (approximate) lower bound for the Lipschitz constant from Combettes & Pesquet (2019), $\| \prod_{i=1}^{d} W_i \|_2$, which lower bounds most available Lipschitz estimates (though it is not strictly a lower bound on the true constant). A naive upper bound can be computed as $\prod_{i=1}^{d} \|W_i\|_2$. We include these naive bounds wherever applicable.

Depth: Fully-connected monDEQs Here, we train DNNs for various depths from $d = 3, 4, \ldots, 14$ for a fixed hidden layer width $h = 40$, and plot (Figure 1a) the bound on the Lipschitz constant given by the SDP-based method of Fazlyab et al. (2019) on these DNNs. We can observe that all estimates of the Lipschitz constant increase exponentially with depth. For comparison, in Figure 1b we plot our Lipschitz constant bounds for monDEQs with fixed $h = 40, 60$, for a range of strong-monotonicity parameters m. We note that the models obtain similar test accuracy to the DNNs. Not only is the Lipschitz constant of the monDEQ much smaller, but we can also observe that on increasing m, the Lipschitz constant of the monDEQ decreases, outlining how we can exercise control on the Lipschitz constant of the monDEQ .

Depth: CNNs and convolutional monDEQs Next, using the bound derived in Section 3.1, we compute the Lipschitz constant of convolutional monDEQ architectures, namely single convolu-



(a) DNN bounds vs Width

(b) monDEQ bounds vs Width

(c) Forward-Backward unrolled Lipschitz bounds

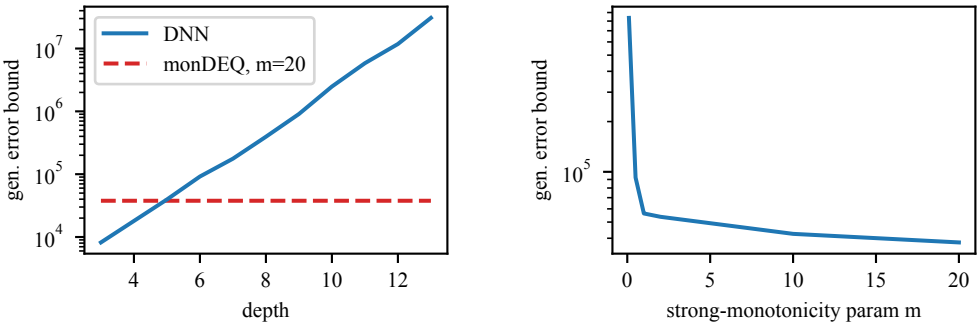
(d) Peaceman-Rachford unrolled Lipschitz bounds

Figure 2: Evaluating Lipschitz bounds as a function of depth or unrolling α.

tional and multi-tier convolutional monDEQs. For comparison, we refer to the numbers in Figure 5 in Virmaux & Scaman (2018), which reports the Lipschitz constants computed by various methods for different CNNs with increasing depth. For our estimate on the single convolutional monDEQ, we use a single convolutional layer with 128 channels, whereas for the multi-tier convolutional monDEQ, we use 3 convolutional layers with 32, 64 and 128 channels. In Figure 1c, we can observe that as for DNNs, the CNN Lipschitz constants estimated by existing methods also suffer with depth. However, we can observe in Figure 1d that the Lipschitz bounds for convolutional monDEQs are much smaller. Also, on increasing m, we can control the Lipschitz constant of both single as well as multi-tier convolutional monDEQs.

Width We compare the Lipschitz constants of monDEQs and DNNs having the same width, for a fixed depth $d = 5$. The DNN numbers are derived from Figure 2(a) in (Fazlyab et al., 2019). We can observe that the Lipschitz constant of the monDEQ for the same width (and essentially infinite depth) is much lower than the bounds for regular DNNs.

Unrolling monDEQs In this experiment, we study if unrolling monDEQs up to a finite depth and constructing an equivalent DNN with this depth leads to a tight estimate of the Lipschitz constant of the monDEQ. Concretely, we do this for two operator splitting methods in the monDEQ: Forward-backward (FB) iterations and Peaceman-Rachford (PR) iterations. For each value of α in a range, we calculate the number of iterations (FB or PR) required for the converge within a specified tolerance 1e-3, and construct the equivalent DNN with this depth. Note that these equivalent unrolled DNNs compute the same function as the monDEQ (up to tolerance), and therefore, must have the same Lipschitz constants of around 10. We compute naive upper bounds on the Lipschitz constants of these DNNs (we cannot use the SDP-based bound of Fazlyab et al. (2019) due to technicalities in the construction of the unrolled DNN; refer to Appendix E). We can observe in Figures 2c, 2d that the upper bounds corresponding to both PR and FB iterations are in the range 10^5 to 10^{13}, suggesting



(a) DNN generalization bound vs Depth

(b) monDEQ generalization bounds vs m

Figure 3: Generalization bounds for DNNs and monDEQs as a function of depth and strong monotonicity parameter.

that unrolling the monDEQ and employing standard techniques on the unrolled monDEQs is not a viable way to bound the Lipschitz constant. More details about the construction of these equivalent DNNs for both FB and PR iterations are provided in Appendix E.

5.2 Generalization bounds

A key advantage of the monDEQ generalization bounds derived in Section 4 is the lack of any depth analog that can cause the bounds to grow exponentially. To assess this aspect experimentally, we first compute the DNN generalization bound following the protocol of Nagarajan & Kolter (2018). We train DNNs (width $= 40$) of varying depth of 3 to 14 layers, and compare to similar monDEQs with various m values. Each model is trained until the margin error at margin $\gamma = 10$ reaches below 10% which serves to standardize the experiments across choice of batch size and learning rate. As widely reported, we see that DNN bounds increase exponentially with depth, ranging numerically from 10^4 for depth 3 networks to 10^8 (see Figure 4a). For monDEQs of width $= 40$ we see that the bound decreases monotonically with m, and is confined to the range 10^4 to 10^6, as seen in Figure 4b (note the difference in scale). In contrast, the true test error of the DNNs increases only slightly with depth, and that of the monDEQs increases only slightly with m. Note that the DNNs and monDEQ s both have comparable test error (see Figures 4a,4b in Appendix G).

Finally, as done for Lipschitz bounds above, we compare our generalization bound to what we obtain by unrolling the monDEQ into a DNN, and then computing the Neyshabur et al. (2018) bound more-or-less directly (see Appendix F for details). We do this only for forward-backward iterations, as the inverted operators of Peaceman-Rachford iterations complicate the analysis. As we see in Figure 4c, the resulting bounds are quite high, though the difference with our bound is not as great as was seen for the unrolled Lipschitz bounds above. We attribute this to the fact that our generalization bound technique is a minimal modification to that of Neyshabur et al. (2018); we expect that it can be significantly tightened with more refined analysis.

6 Conclusion

In this paper, we derived Lipschitz bounds for monotone DEQs, a recently proposed class of impicit-layer networks, and showed that they depend in a straighforward manner on the strong monotonicity parameter m of these networks. Having derived a Lipschitz bound with respect to perturbation in the weights, we were able to derive a PAC-Bayesian generalization bound for the monotone DEQ, which does not depend exponentially on depth. We showed empirically that our bounds are sensible, can be controlled by choosing m suitably, and do not suffer with increasing depth of the network. As future work, we aim to analyze the vacuousness of the derived generalization bound. As such, since our bound does not suffer exponentially with depth, we hope to be able to make the analysis tighter and derive a non-vacuous generalization bound.

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A Proof of Proposition 1

Proof.

$$\begin{aligned}
\|Tx - Ty\|_2^2 &= \|((1-\alpha)I + \alpha W)x - ((1-\alpha)I + \alpha W)y\|_2^2 \\
&= \|x - y - \alpha(I - W)(x - y)\|_2^2 \\
&= \|x - y\|_2^2 - 2\alpha(x-y)^T(I-W)(x-y) + \alpha^2\|(I-W)(x-y)\|_2^2 \\
&\leq \|x - y\|_2^2 - 2\alpha(x-y)^T(I-W)(x-y) + \alpha^2 L[I-W]^2\|x-y\|_2^2
\end{aligned}$$

Now, note that by the strong monotonicity of the monDEQ,

$$I - W \succeq mI,$$

which implies that $(x-y)^T(I-W)(x-y) \geq m\|x-y\|_2^2$. Substituting this bound above, we have that

$$\begin{aligned}
\|Tx - Ty\|_2^2 &\leq \|x-y\|_2^2 - 2\alpha m\|x-y\|_2^2 + \alpha^2 L[I-W]^2\|x-y\|_2^2 \\
&= (1 - 2\alpha m + \alpha^2 L[I-W]^2)\|x-y\|_2^2
\end{aligned}$$

Thus, we have that $L[T] \leq \sqrt{1 - 2\alpha m + \alpha^2 L[I-W]^2}$ □

B Proof of Proposition 2

Proof.

$$\begin{aligned}
\|f_k(W,U,b)\|_2 &= \|\sigma(Tf_{k-1}(W,U,b) + \alpha(Ux+b))\|_2 \\
&\leq \|Tf_{k-1}(W,U,b) + \alpha(Ux+b)\|_2 \quad \text{(ReLU is 1-Lipschitz)} \\
&\leq \|T\|_2\|f_{k-1}(W,U,b)\|_2 + \alpha\|Ux+b\|_2 \\
&\leq L[T]\|f_{k-1}(W,U,b)\|_2 + \alpha\|Ux+b\|_2 \\
&\leq L[T]^k\|f_0(W,U,b)\|_2 + \alpha\|Ux+b\|_2\sum_{i=0}^{k-1} L[T]^i \\
&= \alpha\|Ux+b\|_2\sum_{i=0}^{k-1} L[T]^i \quad \text{(since } f_0(W,U,b) = 0\text{)} \\
&\leq \alpha\|Ux+b\|_2\sum_{i=0}^{\infty} L[T]^i \\
&= \frac{\alpha\|Ux+b\|_2}{1 - L[T]} \quad \text{(since } L[T] < 1\text{)}
\end{aligned}$$

□

C Proof of Theorem 2

Proof. Denote $\bar{f}_k = f_k(\bar{W}, \bar{U}, \bar{b})$ and $f_k = f_k(W,U,b)$. Further, denote $\Delta_k = \|\bar{f}_k - f_k\|_2$. For $\alpha \in \left(0, \min\left(\frac{2m}{L[I-W]^2}, \frac{2\bar{m}}{L[I-\bar{W}]^2}\right)\right)$, we have from Proposition 1 that both $\|T(W)\|_2, \|T(\bar{W})\|_2 <$

1. Thus,

$$
\begin{aligned}
\Delta_k &= \|\sigma[T(\bar{W})\bar{f}_{k-1} + \alpha(\bar{U}x + \bar{b})] - \sigma[T(W)f_{k-1} + \alpha(Ux + b)]\|_2 \\
&\leq \|T(\bar{W})\bar{f}_{k-1} - T(W)f_{k-1} + \alpha(\bar{U} - U)x + \alpha(\bar{b} - b)\|_2 \\
&\leq \|T(\bar{W})(\bar{f}_{k-1} - f_{k-1}) + (T(\bar{W}) - T(W))f_{k-1} + \alpha(\bar{U} - U)x + \alpha(\bar{b} - b)\|_2 \\
&\leq \|T(\bar{W})(\bar{f}_{k-1} - f_{k-1}) + \alpha(\bar{W} - W)f_{k-1} + \alpha(\bar{U} - U)x + \alpha(\bar{b} - b)\|_2 \\
&\leq \|T(\bar{W})\|_2\Delta_{k-1} + \alpha\|\bar{W} - W)\|_2\|f_{k-1}\|_2 + \alpha\|(\bar{U} - U)x\|_2 + \alpha\|\bar{b} - b\|_2 \\
&\leq \|T(\bar{W})\|_2\Delta_{k-1} + \frac{\alpha^2\|\bar{W} - W)\|_2\|Ux + b\|_2}{1 - \|T(W)\|_2} + \alpha\|(\bar{U} - U)x\|_2 + \alpha\|\bar{b} - b\|_2 \quad \text{(Proposition 2)} \\
&\leq \left(\frac{\alpha^2\|\bar{W} - W)\|_2\|Ux + b\|_2}{1 - \|T(W)\|_2} + \alpha\|(\bar{U} - U)x\|_2 + \alpha\|\bar{b} - b\|_2\right)\sum_{i=0}^{k-1}\|T(\bar{W})\|_2^i
\end{aligned}
$$

Notice here again that the above inequality holds for all k. Taking the limit as $k \to \infty$ similar to the step in the proof of Theorem 1, we have

$$
\begin{aligned}
\|f(\bar{W}, \bar{U}, \bar{b}) - f(W, U, b)\|_2 &= \lim_{k\to\infty} \Delta_k \\
&\leq \left(\frac{\alpha^2\|\bar{W} - W)\|_2\|Ux + b\|_2}{1 - \|T(W)\|_2} + \alpha\|(\bar{U} - U)x\|_2 + \alpha\|\bar{b} - b\|_2\right)\sum_{i=0}^{\infty}\|T(\bar{W})\|_2^i \\
&= \frac{\alpha^2\|\bar{W} - W)\|_2\|Ux + b\|_2}{(1 - \|T(W)\|_2)(1 - \|T(\bar{W})\|_2)} + \alpha\frac{\|(\bar{U} - U)x\|_2 + \|\bar{b} - b\|_2}{1 - \|T(\bar{W})\|_2}
\end{aligned}
$$

Finally, taking $\alpha \to 0$, we have that

$$
\begin{aligned}
\|f(\bar{W}, \bar{U}, \bar{b}) - f(W, U, b)\|_2 &\leq \lim_{\alpha\to 0}\left(\frac{\alpha^2\|\bar{W} - W)\|_2\|Ux + b\|_2}{(1 - \|T(W)\|_2)(1 - \|T(\bar{W})\|_2)} + \right. \\
&\qquad \left. \alpha\frac{\|(\bar{U} - U)x\|_2 + \|\bar{b} - b\|_2}{1 - \|T(\bar{W})\|_2}\right) \\
&= \|\bar{W} - W)\|_2\|Ux + b\|_2 \lim_{\alpha\to 0}\frac{\alpha}{1 - \|T(W)\|_2} \cdot \lim_{\alpha\to 0}\frac{\alpha}{1 - \|T(\bar{W})\|_2} \\
&\qquad + (\|(\bar{U} - U)x\|_2 + \|\bar{b} - b\|_2)\lim_{\alpha\to 0}\frac{\alpha}{1 - \|T(\bar{W})\|_2} \\
&= \frac{\|\bar{W} - W\|_2\|Ux + b\|_2}{m\bar{m}} + \frac{\|(\bar{U} - U)x\|_2 + \|\bar{b} - b\|_2}{\bar{m}} \quad \text{(applying L'Hopital's rule)}
\end{aligned}
$$

□

D PROOF OF THEOREM 3

Proof. We first state Lemma 1 from Neyshabur et al. (2018).

Lemma 1 (Lemma 1 from Neyshabur et al. (2018))**.** *Let f_w be any predictor with parameters w, and let P denote any distribution on the parameters that is independent of the training data. Then, for any $\delta, \gamma > 0$, with probability $\geq 1 - \delta$ over the training data of size M, for any w, and any random perturbation u such that $\mathbb{P}[\max_x \|f_{w+u}(x) - f_w(x)\|_\infty < \frac{\gamma}{4}] \geq \frac{1}{2}$, we have*

$$
L_0(f_w) \leq \hat{L}_\gamma(f_w) + 4\sqrt{\frac{KL(w + u||P) + \ln\frac{6M}{\delta}}{M - 1}}
$$

Now, we derive a perturbation bound for the monDEQ when we incorporate the a fully connected layer at the end, as mentioned in Section 4. That is, we consider $f_o(x) = W_o f(x) + b_0$ where f is the output of the fixed-point iterations of the monDEQ. Next, we consider perturbations $\Delta_A, \Delta_B, \Delta_U, \Delta_b, \Delta_{W_o}, \Delta_{b_o}$ for A, B, U, b, W_o, b_o respectively. The entries in the perturbation matrices are each drawn independently from a Gaussian $\mathcal{N}(0, \sigma^2)$. Let $\bar{f}_o$ to denote the function at the

perturbed values of the weights. Then, we have that

$$\begin{aligned}\|\bar{f}_o(x) - f_o(x)\|_2 &= \|\bar{W}_o\bar{f}(x) + \bar{b}_o - W_o f(x) - b_o\|_2 \\ &\leq \|W_o(\bar{f}(x) - f(x)) + (\bar{W}_o - W_o)\bar{f}(x)\|_2 + \|\bar{b}_o - b_o\|_2 \\ &\leq \|W_o\|_2\Delta + \frac{\|\bar{W}_o - W_o\|_2\|Ux + b\|_2}{\bar{m}} + \|\bar{b}_o - b_o\|_2\end{aligned}$$

where Δ is the bound from Theorem 2.

Now, let $\beta = \max(\|U\|_2, \|A\|_2, \|W_o\|_2, \|b\|_2)$. Just as in (Neyshabur et al., 2018), since we cannot use β in determining the parameters of the prior distribution P in Lemma 1, we will consider predetermined values $\tilde{\beta}$ on a grid, and then do a union bound. For now, we fix $\tilde{\beta}$, and consider all the values β such that $|\beta - \tilde{\beta}| < c_1\beta$ for some constant $c_1 < 1$.

Since the entries in the perturbations are drawn from $\mathcal{N}(0, \sigma^2)$, we have the following bound on the l_2 norms of these perturbations:

$$\mathbb{P}_{\Delta_\cdot \sim \mathcal{N}(0,\sigma^2 I)}[\|\Delta_\cdot\|_2 > t] \leq 2he^{-t^2/2h\sigma^2}$$

where $\Delta_\cdot$ is a placeholder for each of the perturbation matrices. Thus, we have that with probability $\geq$ 1/2, all of the $\|\Delta_\cdot\|_2$ are bounded above by $\sigma\sqrt{2h\ln(24h)} := \omega$.

Now, we bound the perturbation in $\|W\|_2$ when A and B are perturbed. We have that

$$\begin{aligned}\|\Delta_W\|_2 &= \|A^T\Delta_A + \Delta_A^T A + \Delta_A^T\Delta_A + \Delta_B - \Delta_B^T\|_2 \\ &\leq 2\|A\|_2\|\Delta_A\|_2 + \|\Delta_A\|_2^2 \\ &\leq 2\omega(\beta + \omega) \quad \text{(with probability 1/2)}\end{aligned}$$

Substituting this above, we have that for all x, with probability at least $1/2$,

$$\|\bar{f}_o(x) - f_o(x)\|_2 \leq \frac{2\beta^2\omega(\beta+\omega)(B+1)}{m^2} + \frac{2\omega\beta(B+1)}{m} + \omega$$

Here, let $c_2 > 0$ be some constant such that $\omega \leq c_2\beta$. Thus, we have that

$$\begin{aligned}\|\bar{f}_o(x) - f_o(x)\|_2 &\leq \omega\left(\frac{2\beta^3(1+c_2)(B+1)}{m^2} + \frac{2\beta(B+1)}{m} + 1\right) \\ &\leq \omega\left(\frac{2\tilde{\beta}^3(1+c_2)(B+1)}{m^2(1-c_1)^3} + \frac{2\tilde{\beta}(B+1)}{m(1-c_1)} + 1\right) \\ &= \sigma\sqrt{2h\ln(24h)}\left(\frac{2\tilde{\beta}^3(1+c_2)(B+1) + 2m\tilde{\beta}(B+1)(1-c_1)^2 + m^2(1-c_1)^3}{m^2(1-c_1)^3}\right)\end{aligned}$$

Setting $\sigma = \frac{\gamma m^2(1-c_1)^3}{4\sqrt{2h\ln(24h)}(2\tilde{\beta}^3(1+c_2)(B+1)+2m\tilde{\beta}(B+1)(1-c_1)^2+m^2(1-c_1)^3)}$ makes this $\leq \frac{\gamma}{4}$. Since we need $\omega \leq c_2\beta$ we can take the smallest c_2 such that

$$c_2 \geq \frac{(1+c_1)\sigma\sqrt{2h\ln(24h)}}{\tilde{\beta}} \geq \frac{\sigma\sqrt{2h\ln(24h)}}{\beta} = \frac{\omega}{\beta}$$

Taking $c_2 = \frac{(1+c_1)\gamma}{4\tilde{\beta}}$ suffices. We will later plug in the value

$$c_3 := \frac{(1+c_1)\gamma}{4(1-c_1)\beta} \geq c_2$$

to bound c_2.

Then,

$$\begin{aligned}&KL(W_\cdot + \Delta_{W_\cdot}|P) \leq \frac{\sum\|W_\cdot\|_F^2}{2\sigma^2} \\ &= \frac{16h\ln(24h)(2\tilde{\beta}^3(1+c_2)(B+1) + 2m\tilde{\beta}(B+1)(1-c_1)^2 + m^2(1-c_1)^3)^2}{\gamma^2 m^4(1-c_1)^6}\sum\|W_\cdot\|_F^2 \\ &\leq \frac{16h\ln(24h)(2\beta^3(1+c_1)^3(1+c_3)(B+1) + 2m\beta(1+c_1)(B+1)(1-c_1)^2 + m^2(1-c_1)^3)^2}{\gamma^2 m^4(1-c_1)^6}\sum\|W_\cdot\|_F^2\end{aligned}$$

Then, by Lemma 1, we have that with probability $1-\delta$,

$$L_0(f_0) \leq \hat{L}_\gamma(f_o) + 4\sqrt{\frac{16h\ln(24h)(2\beta^3(1+c_1)^3(1+c_3)(B+1)+2m\beta(1+c_1)(B+1)(1-c_1)^2+m^2(1-c_1)^3)^2}{\gamma^2 m^4(1-c_1)^6(M-1)}\sum\|W_\cdot\|_F^2 + \frac{\ln(\frac{6M}{\delta})}{M-1}}$$

Now we need to take a union bound over $\tilde{\beta}$ so that the above result holds for all β. Observe that we only need to consider β in the range

$$\frac{\gamma m}{2(B+1)} \leq \beta \leq \frac{\gamma m\sqrt{M}}{2(B+1)}.$$

If $\beta \leq \frac{\gamma m}{2(B+1)}$ then $|f(x)| \leq \frac{\beta(B+1)}{m} \leq \frac{\gamma}{2}$ so $\hat{L}_\gamma(f) > 1$. If $\beta \geq \frac{\gamma m\sqrt{M}}{2(B+1)}$ then the second term in the first term in the numerator is greater than 1 so the theorem holds trivially.

So $|\beta - \tilde{\beta}| \leq c_1\frac{\gamma m}{2(B+1)}$ guarantees $|\beta-\tilde{\beta}| \leq c_1\beta$ in this range. So we can use a cover of size $\sqrt{M}/2c_1$: This amounts to replacing $\ln 6M/\delta$ with $\ln 3M^{3/2}/c_1\delta$.

Finally, substituting $c_3 = \frac{(1+c_1)\gamma}{4(1-c_1)\beta}$, we get the theorem statement. We can also effectively optimize over c_1 to remove it from the final bound. □

E Unrolling Forward-Backward and Peaceman-Rachford iterations

In this section, we derive the form of the equivalent feedforward DNN after k iterations of either Forward-Backward or Peaceman-Rachford iterations.

E.1 Unrolling Forward-Backward Iterations

One step in the Forward-Backward iterations computes

$$z^{(i+1)} = \sigma((1-\alpha)I + \alpha W)z^{(i)} + \alpha(Ux+b))$$

Now, let us construct the following matrices:

$$W_1 = [\alpha U \quad I]$$
$$W_u = \begin{bmatrix}(1-\alpha)I+\alpha W & \alpha U \\ 0 & I\end{bmatrix}$$
$$W_f = [W_o \quad 0]$$

Then, we can observe that

$$z^{(1)} = \sigma\left(W_1 x + \begin{bmatrix}\alpha b \\ 0\end{bmatrix}\right)$$
$$z^{(i+1)} = \sigma\left(W_u\begin{bmatrix}z^{(i)} \\ x\end{bmatrix} + \begin{bmatrix}\alpha b \\ 0\end{bmatrix}\right)$$

Here, σ applies only to the $z^{(i)}$ coordinates. Finally, if we want the output of the monDEQ after k iterations, we obtain

$$f_0(x) = W_f\begin{bmatrix}z^{(k)} \\ x\end{bmatrix} + b_o$$

Thus, the equivalent depth-k DNN which we construct would have weight matrices $W_1, [W_u]_{i=1}^{k-1}, W_f$, and the ReLUs in the intermediate layers would only apply to the top coordinates corresponding to z (this is the technical reason why we can't use the SDP bound given by (Fazlyab et al., 2019) for computing the Lipschitz constants of these unrolled networks, since they require the same nonlinearity to apply pointwise at all coordinates).

E.2 UNROLLING PEACEMAN-RACHFORD ITERATIONS

Define $V = (I + \alpha(I - W))^{-1}$. One step in the Peaceman-Rachford iterations computes

$$\begin{aligned} u^{(i+1)} &= u^{(i)} - 2z^{(i)} + 4Vz^{(i)} - 2Vu^{(i)} + 2\alpha VUx + 2\alpha Vb \\ z^{(i+1)} &= \sigma(u^{i+1}) \end{aligned}$$

Let us construct the following matrices:

$$\begin{aligned} W_1 &= [2\alpha VU \quad 2\alpha VU \quad I] \\ W_u &= \begin{bmatrix} I - 2V & 4V - 2I & 2\alpha VU \\ I - 2V & 4V - 2I & 2\alpha VU \\ 0 & 0 & I \end{bmatrix} \\ W_f &= [0 \quad W_o \quad 0] \end{aligned}$$

Then, we can observe that

$$\begin{aligned} z^{(1)} &= \sigma\left(W_1 x + \begin{bmatrix} 2\alpha Vb \\ 2\alpha Vb \\ 0 \end{bmatrix}\right) \\ z^{(i+1)} &= \sigma\left(W_u \begin{bmatrix} u^{(i)} \\ z^{(i)} \\ x \end{bmatrix} + \begin{bmatrix} 2\alpha Vb \\ 2\alpha Vb \\ 0 \end{bmatrix}\right) \end{aligned}$$

Here, the σ applies only to the $z^{(i)}$ coordinates. Finally, if we want the output of the monDEQ after k iterations, we obtain

$$f_0(x) = W_f \begin{bmatrix} u^{(k)} \\ z^{(k)} \\ x \end{bmatrix} + b_o$$

Thus, the equivalent depth-k DNN which we construct would have weight matrices $W_1, [W_u]_{i=1}^{k-1}, W_f$, and the ReLUs in the intermediate layers would only apply to the top coordinates corresponding to z.

F GENERALIZATION BOUND FOR UNROLLED MONDEQ

In this section, we derive a generalization bound for an unrolled monDEQ after unrolling the forward-backward iterations d times and constructing the equivalent depth-d network. The analysis follows the derivation of the generalization bound for DNNs by (Neyshabur et al., 2018), but we have to be careful since the weight matrices across the hidden layers are all the same and are of a certain parameterized form. Since the analysis in (Neyshabur et al., 2018) does not include biases in the DNNs, here, we consider unrolling monDEQs which do not have the bias term b.

Take each layer weights to be

$$W_u = \begin{bmatrix} I - \alpha(I - W) & \alpha U \\ 0 & I \end{bmatrix}$$

where the network is now a function of

$$\bar{z}_i := \begin{bmatrix} z^{(i)} \\ x \end{bmatrix}$$

and the ReLU applies only to the $z^{(i)}$ component. And

$$W_f = \begin{bmatrix} W_o \\ 0 \end{bmatrix}$$

Our prior distribution will now be over $\Delta_{W_o}, \Delta_A, \Delta_B, \Delta_U \sim \mathcal{N}(0, \sigma^2 I)$. Similar to the corresponding step in D above, we have that with probability $\geq \frac{1}{2}$, the perturbations are each bounded by $\omega := \sigma\sqrt{2h\ln(16h)}$. Also

$$\begin{aligned} \|\Delta_W\|_2 &= \|\bar{A}^T\bar{A} - A^T A + \bar{B} - B - \bar{B}^T + B^T\|_2 \\ &\leq \|\Delta_A\|_2^2 + 2\|\Delta_A\|_2\|A\|_2 + 2\|\Delta_B\|_2 \end{aligned}$$

And so

$$\|\Delta_{W_u}\|_2 = \left\| \begin{bmatrix} \alpha\Delta_W & \alpha\Delta_U \\ 0 & 0 \end{bmatrix} \right\|_2$$
$$\leq \alpha \left(\|\Delta_A\|_2^2 + 2\|\Delta_A\|_2\|A\|_2 + 2\|\Delta_B\|_2 + \|\Delta_U\|_2 \right)$$

We take $\beta = \max\{\|A\|_2, \|B\|_2, \|W_u\|_2, \|W_o\|_2\}$. We assume that $|\tilde{\beta} - \beta| \leq \frac{1}{d}\beta$ and $d \geq 2$, so we have $\beta < e\tilde{\beta}$. Then applying Lemma 2 in (Neyshabur et al., 2018), we have

$$\begin{aligned}
|f_{W_u+\Delta_{W_u}} - f_{W_u}|_2 &\leq eB\beta^{d-1}((d-1)\|\Delta_{W_u}\|_2 + \|\Delta_{W_o}\|_2) \\
&\leq eB\beta^{d-1}((d-1)\alpha \left(\|\Delta_A\|_2^2 + 2\|\Delta_A\|_2\|A\|_2 + 2\|\Delta_B\|_2 + \|\Delta_U\|_2 \right) + \|\Delta_{W_o}\|_2) \\
&\leq eB\beta^{d-1}((d-1)\alpha(\omega^2 + 2\omega\beta + 3\omega) + \omega) \\
&\leq eB\beta^{d-1}((d-1)\alpha(\frac{1}{d}\beta + 2\beta + 3) + 1)\omega \\
&\leq e^2B\tilde{\beta}^{d-1}((d-1)\alpha(\frac{e}{d}\tilde{\beta} + 2e\tilde{\beta} + 3) + 1)\sigma\sqrt{2h\ln(16h)} \leq \frac{\gamma}{4}
\end{aligned}$$

if we choose

$$\sigma = \frac{\gamma}{4e^2B\tilde{\beta}^{d-1}((d-1)\alpha(\frac{e}{d}\tilde{\beta} + 2e\tilde{\beta} + 3) + 1)\sqrt{2h\ln(16h)}}.$$

Let

$$\sum \|W_\cdot\|_F^2 = \|A\|_F^2 + \|B\|_F^2 + \|U\|_F^2 + \|W_o\|_F^2$$

Then

$$\begin{aligned}
\mathrm{KL}(A + \Delta_A, B + \Delta_B, U + \Delta_U, W_o + \Delta_{W_o})\|P) &\leq \frac{\sum |A, B, U, W_o|_F^2}{2\sigma^2} \\
&= \frac{16e^4B^2\tilde{\beta}^{2d-2}((d-1)\alpha(\frac{e}{d}\tilde{\beta} + 2e\tilde{\beta} + 3) + 1)^2 2h\ln(16h)}{\gamma^2} \sum \|W_\cdot\|_F^2 \\
&\leq \frac{16e^2B^2\beta^{2d-2}((d-1)\alpha(\frac{1}{d}\beta + 2\beta + 3) + 1)^2 2h\ln(16h)}{\gamma^2} \sum \|W_\cdot\|_F^2
\end{aligned}$$

Now, instantiating Lemma 1 above, we have that with probability at least $1 - \delta$,

$$L_0(f) \leq \hat{L}_\gamma(f) + 4\sqrt{\frac{16e^2B^2\beta^{2d-2}((d-1)\alpha(\frac{1}{d}\beta + 2\beta + 3) + 1)^2 2h\ln(16h)\sum \|W_\cdot\|_F^2}{\gamma^2(M-1)} + \frac{\ln(\frac{6M}{\delta})}{M-1}}$$

Following Neyshabur et al. (2018), we need to take a union bound over $\tilde{\beta}$ so that the above result holds for all β. Observe that we only need to consider β in the range

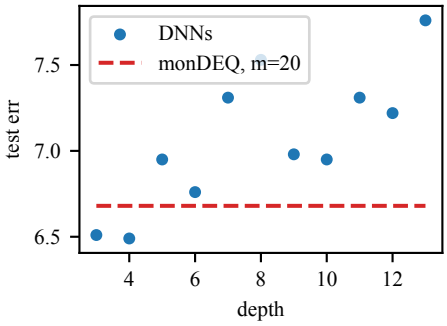
$$\left(\frac{\gamma}{2B}\right)^{1/d} \leq \beta \leq \left(\frac{\gamma\sqrt{M}}{2B}\right)^{1/d}.$$

If $\beta^d \leq \frac{\gamma m}{2B}$ then $|f(x)| \leq \beta^d B \leq \frac{\gamma}{2}$ so $\hat{L}_\gamma(f) > 1$. If $\beta^d \geq \frac{\gamma\sqrt{M}}{2B}$ then the second term in the first term in the numerator is greater than 1 so the result holds trivially. So $|\beta - \tilde{\beta}| \leq \frac{1}{d}\left(\frac{\gamma}{2B}\right)^{1/d}$ guarantees $|\beta - \tilde{\beta}| \leq \frac{1}{d}\beta$ in this range. So we can use a cover of size $dM^{1/2d}$, just as in Neyshabur et al. (2018).

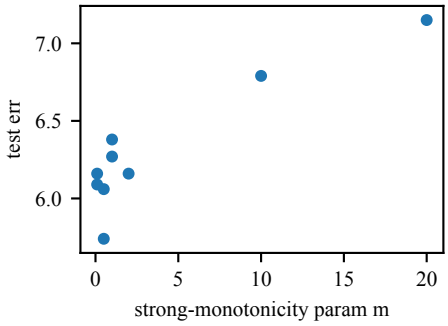
G Additional monDEQ generalization bound results

Here, we validate that both the monDEQ and DNN models considered in Section 5.2 for generalization bound comparisons indeed achieve comparable accuracy as well. Figures 4a, 4b illustrate this: we can observe that the various models considered all achieve test error in the same range.

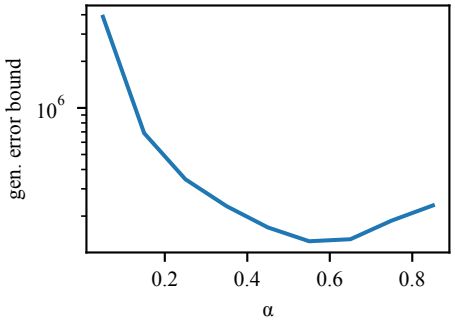
Next, we compute generalization bounds for unrolled monDEQs (Section F) for a variety of α values, to get a sense of the quality of our generalization bound for the monDEQ. In Figure 4c, we can observe that the generalization bounds for these unrolled networks are larger (on the order of 10^6) as compared to the generalization bound for the monDEQ (on the order 10^5). This shows that our bound is tighter.



(a) DNN Test error vs Depth



(b) monDEQ Test error vs m



(c) Forward-Backward unrolled generalization bound

Figure 4: Test error for DNNs and monDEQ s, and monDEQ generalization bounds by unrolling forward-backward iterations.