Exploring the Loss Landscape of Regularized Neural Networks via Convex Duality

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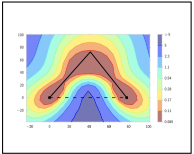
Loss Landscape and Global Minima

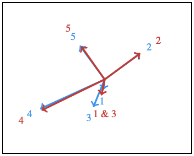
Loss Landscape and Global Minima

Mode Connectivity



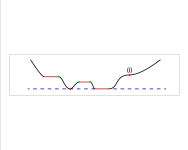
Garipov et al. (2018)

Permutation Symmetry



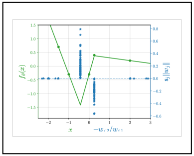
Brea et al. (2019)

Benign Landscape



Vidal et al. (2022)

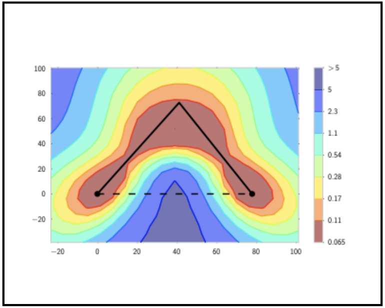
Unique Interpolator



Boursier and Flammarion (2023)

Loss Landscape and Global Minima

Mode Connectivity

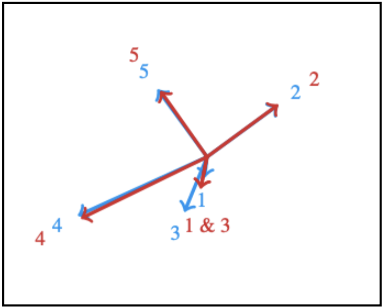


Garipov et al. (2018)

- Two different solutions are connected by a very simple curve.

Loss Landscape and Global Minima

Permutation Symmetry

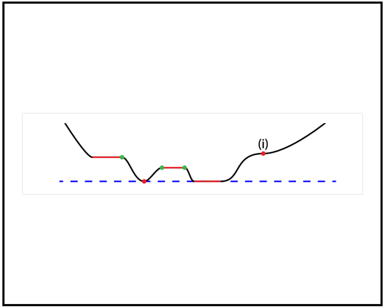


Brea et al. (2019)

- Permutations of an optimal neural network is still optimal.
- They are connected with a smooth path with low training loss.

Loss Landscape and Global Minima

Benign Landscape

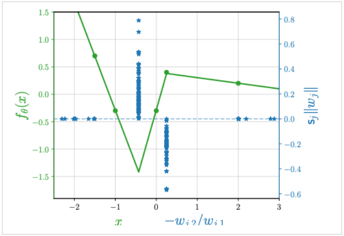


Vidal et al. (2022)

- For sufficiently wide neural networks, there is always a decreasing path to a global optimum.

Loss Landscape and Global Minima

Unique Interpolator



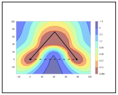
Boursier and Flammarion (2023)

- Penalizing the bias and using free skip connections (e.g. an unregularized linear neuron).

Our Contributions

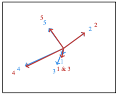
Existing Work

Mode Connectivity



Garipov et al. (2018)

Permutation Symmetry



Brea et al. (2019)

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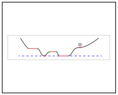

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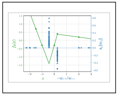
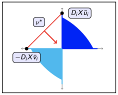
Unique Interpolator



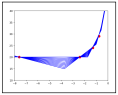
Boursier and Flammarion (2023)

"Our Contributions"

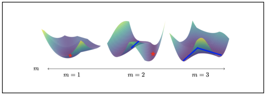
Dual Geometry



Continuum of Interpolators



Staircase of Connectivity



We extend our knowledge on the loss landscape and global minima of neural networks via **the convex optimization perspective**.

We use an equivalent convex optimization problem to...

- discuss **novel geometric insights** of the global minima
- **phase transition in the connectivity** as the width changes
- construct a **continuum of optimal interpolators** with regularized bias.

Extensions to vector-valued networks, parallel three-layer networks, etc.

In this talk...

We use an equivalent convex optimization problem to...

- discuss **novel geometric insights** of the global minima
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Extensions to vector-valued networks, parallel three-layer networks, et cetera.

Background: Convex Neural Networks

- Let $X \in \mathbb{R}^{n \times d}$ be the data matrix, $y \in \mathbb{R}^n$ be the labels, $u_j \in \mathbb{R}^d$, $\alpha_j \in \mathbb{R}$ for $j = 1, 2, \cdots m$, and $\beta > 0$.
- We use $(\cdot)_+$ to denote the ReLU activation.
- Also, $L : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}_{\geq 0}$ is a convex loss function.

Our primary interest: "two-layer", "scalar-output", "ReLU - activation", "weight decay"

Background: Convex Neural Networks

The objective of interest can be written as

$$\min_{u_j \in \mathbb{R}^d, \alpha_j \in \mathbb{R}} \; L\Big(\sum_{j=1}^{m} (Xu_j)_+ \alpha_j, y\Big) + \frac{\beta}{2} \sum_{j=1}^{m} (\|u_j\|_2^2 + \|\alpha_j\|_2^2).$$

Notation

We will use the term "nonconvex objective" to refer to the above problem. Also, the optimal objective will be noted as p^*_{noncvx} and the set of optimal parameters will be noted as Θ^*_m.

The Convex Reformulation

Pilanci and Ergen (2020) showed that if $m \geq m^*$ for some critical width m^*, there exists an **equivalent convex optimization problem**.

- When we denote p^*_{cvx} as the optimal objective of the convex problem,

$$p^*_{\text{cvx}} = p^*_{\text{noncvx}}$$

- There exists a mapping between the optimal solution of the nonconvex objective and the equivalent convex problem (Pilanci and Ergen (2020), Wang et al. (2021)).

The Convex Reformulation

The equivalent convex optimization problem is written as

$$\min_{u_i, v_i} \; L\Big(\sum_{i=1}^{P} D_i X(u_i - v_i), y\Big) + \beta \sum_{i=1}^{P} (\|u_i\|_2 + \|v_i\|_2),$$

subject to constraints $(2D_i - I)Xu_i \geq 0, \; (2D_i - I)Xv_i \geq 0.$

- Here, $D_i = Diag(1(Xh \geq 0))$ denote all possible "hyperplane arrangement patterns"
- Intuition: in the constraint set, ReLU becomes linear and

$$(Xu_i)_+ = D_i X u_i, \quad (Xv_i)_+ = D_i X v_i.$$

The Convex Reformulation

The equivalent convex optimization problem is written as

$$\min_{u_i, v_i} \; L\Big(\sum_{i=1}^{P} D_i X(u_i - v_i), y\Big) + \beta \sum_{i=1}^{P} (\|u_i\|_2 + \|v_i\|_2),$$

subject to constraints $(2D_i - I)Xu_i \geq 0, \; (2D_i - I)Xv_i \geq 0.$

Notation

We will use the term "convex reformulation" to refer to the above problem. Also, the optimal objective will be noted as p^*_{cvx} and the set of optimal parameters will be noted as $\mathcal{P}^*$.

The Dual Problem

The dual of the convex reformulation can be written as

$$\max_{\nu \in \mathbb{R}^n} -L^*(\nu) \quad \text{subject to} \quad |\nu^T (Xu)_+| \leq \beta \quad \forall \|u\|_2 \leq 1.$$

Here, L^* is the Fenchel conjugate of $L(\cdot, y)$.

- Denote the optimal objective of the dual problem as d^*_{cvx}.
- If $m \geq m^*$,

$$p^*_{\text{cvx}} = d^*_{\text{cvx}} = p^*_{\text{noncvx}}.$$

Optimal Set Characterization

Mishkin and Pilanci (2023) show that for strictly convex L,

- $\mathcal{P}^*$ is a polyhedral set
- For $(u_i, v_i)_{i=1}^P, (u_i', v_i')_{i=1}^P \in \mathcal{P}^*$, if both u_i, u_i' are nonzero, they are positive scalings of each other.
- Θ_m^* can be characterized up to permutation/splitting symmetries.
- Our work largely builds upon this characterization, and many concepts needed for proof were adapted.

Optimal Polytope and the Dual Optimum

Theorem (The Optimal Polytope, informal)

Suppose L is a strictly convex loss function. The directions of optimal parameters of the convex problem, noted as $\bar{u}_i, \bar{v}_i$**, are uniquely determined from the dual optimum** ν^**. Moreover, the solution set is the* **polytope**,

$$\mathcal{P}^* = \left\{ (c_i \bar{u}_i, d_i \bar{v}_i)_{i=1}^{P} \mid c_i, d_i \geq 0 \quad \forall i \in [P], \quad \sum_{i=1}^{P} D_i X \bar{u}_i c_i - D_i X \bar{v}_i d_i = y^* \right\}$$

for the unique optimal model fit y^**.*

- Either $u_i^* = 0$ ($v_i^* = 0$), or
- They are positive scalings of the solution to the optimization problem,

$$\max_{\|u\|_2 \leq 1} |(\nu^*)^T (Xu)_+|,$$

Geometric Intuition: The Rectified Ellipsoid

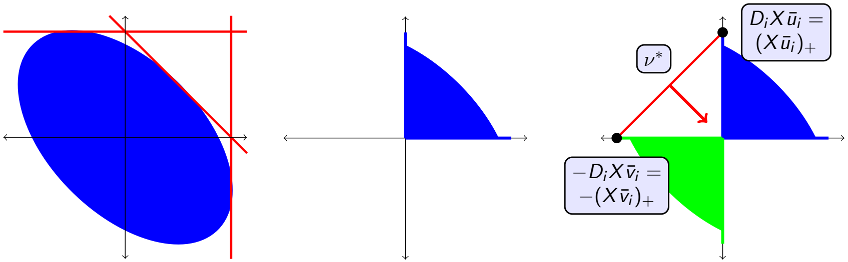
Definition (Pilanci and Ergen (2020))

The rectified ellipsoid is defined as the set

$$\mathcal{Q}_X = \left\{ (Xu)_+ \mid \|u\|_2 \leq 1 \right\}.$$

- It is the image of the ReLU mapping of the ellipsoid $\mathcal{E}_X = \{Xu \mid \|u\|_2 \leq 1\}$.

Geometric Intuition: The Rectified Ellipsoid



(a) $\mathcal{E}_X$ (b) $\mathcal{Q}_X$ (c) $\mathcal{Q}_X \cup -\mathcal{Q}_X$

- The dual variable ν^* **decides the "face"** where the points $\{D_i X \bar{u}_i\}_{i=1}^P \cup \{-D_i X \bar{v}_i\}_{i=1}^P$ lies on.
- Blue set corresponds to $\bar{u}_i$, green set corresponds to $\bar{v}_i$.

The Staircase of Connectivity: Motivation

- Denote $\text{card}((u_i, v_i)_{i=1}^P)$ as the number of nonzero vectors in $\{u_i\}_{i=1}^P \cup \{v_i\}_{i=1}^P$.
- A solution map exists between Θ_m^* and the cardinality - constrained set

$$\mathcal{P}_m^* = \left\{ (u_i, v_i)_{i=1}^P \in \mathcal{P}^* \mid \text{card}((u_i, v_i)_{i=1}^P) \leq m \right\}.$$

The Staircase of Connectivity: Motivation

- Though $\mathcal{P}^*$ is a connected set, $\mathcal{P}^*_m$ **might not be connected** due to cardinality constraints - phase transitional behavior in connectivity!
- As Θ^*_m and $\mathcal{P}^*_m$ are related by the solution map, connectivity properties of Θ^*_m can be deduced from that of $\mathcal{P}^*_m$.

The Staircase of Connectivity

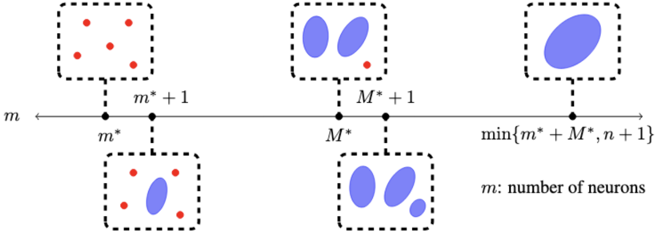


Figure: A schematic for the staircase of connectivity

- Red dots : isolated points, blue sets : connected components with more than one point.
- Critical widths m^*, M^* governs the phase transition.

The Staircase of Connectivity

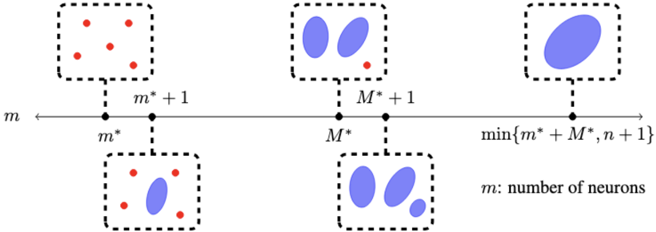


Figure: A schematic for staircase of connectivity

- When $m = m^*$, Θ_m^* is a set of finite isolated points.

The Staircase of Connectivity

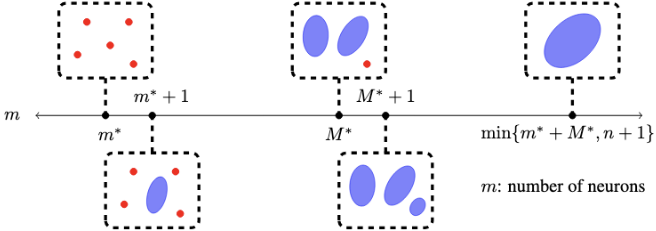


Figure: A schematic for staircase of connectivity

- When $m \geq m^* + 1$, there exists a path between two different optimal solutions in Θ^*_m

The Staircase of Connectivity

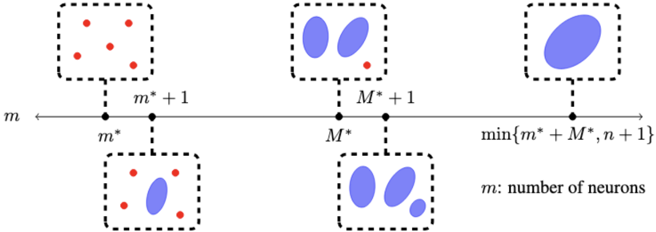


Figure: A schematic for staircase of connectivity

- When $m = M^*$, there exists an isolated point in Θ^*_m.

The Staircase of Connectivity

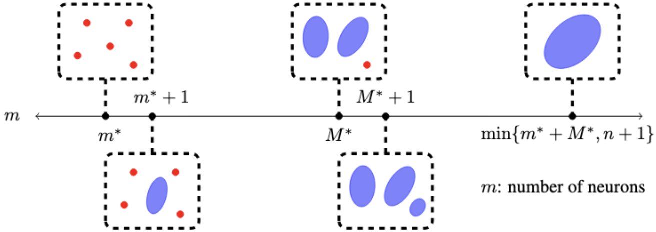


Figure: A schematic for staircase of connectivity

- When $m \geq M^* + 1$, there is no isolated point in Θ_m^*.
- Moreover, for an optimal solution $(w_i, \alpha_i)_{i=1}^m$, any permutation $(w_{\sigma(i)}, \alpha_{\sigma(i)})_{i=1}^m$ has a path inside Θ_m^* that connects the two solutions.

The Staircase of Connectivity

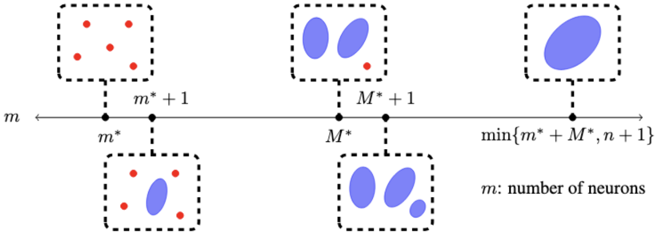


Figure: A schematic for staircase of connectivity

- When $m \geq \min\{M^* + m^*, n+1\}$, Θ_m^* is connected.

Relations with Existing Landscape Results

- Haeffele and Vidal (2017) shows that when $m \geq n+1$, there is no spurious local minima. We further characterize that all sublevel sets are connected.
- Nguyen (2021) shows that when there is no regularization, Θ_m^* is connected when $m \geq n+1$. We extend the result to the regularized case.
- Our analysis is also tightly connected to Simsek et al. (2021), who add a neuron to connect permutations of optimal solutions.

Conclusion

- We derived novel characterizations of the loss landscape and global minima of neural networks by leveraging tools from convex optimization.
- An extension of these results to different nonconvex problems that has convex reformulations could be an interesting future direction.

Poster session: Hall 3 + Hall 2B #350, today 3pm – 5:30pm

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