

# Novelty Assessment Report

**Paper:** Characterizing the Discrete Geometry of ReLU Networks

**PDF URL:** <https://openreview.net/pdf?id=TgLW2DiRDG>

**Venue:** ICLR 2026 Conference Submission

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## Abstract

It is well established that ReLU networks define continuous piecewise-linear functions, and that their linear regions are polyhedra in the input space. These regions form a complex that fully partitions the input space. The way these regions fit together is fundamental to the behavior of the network, as nonlinearities occur only at the boundaries where these regions connect. However, relatively little is known about the geometry of these complexes beyond bounds on the total number of regions, and calculating the complex exactly is intractable for most networks. In this work, we prove new theoretical results about these complexes that hold for all fully-connected ReLU networks, specifically about their connectivity graphs in which nodes correspond to regions and edges exist between each pair of regions connected by a face. We find that the average degree of this graph is upper bounded by twice the input dimension regardless of the width and depth of the network, and that the diameter of this graph has an upper bound that does not depend on input dimension, despite the number of regions increasing exponentially with input dimension. We corroborate our findings through experiments with networks trained on both synthetic and real-world data, which provide additional insight into the geometry of ReLU networks.

### Disclaimer

This report is **AI-GENERATED** using Large Language Models and WisPaper (a scholar search engine). It analyzes academic papers' tasks and contributions against retrieved prior work. While this system identifies **POTENTIAL** overlaps and novel directions, **ITS COVERAGE IS NOT EXHAUSTIVE AND JUDGMENTS ARE APPROXIMATE**. These results are intended to assist human reviewers and **SHOULD NOT** be relied upon as a definitive verdict on novelty.

Note that some papers exist in multiple, slightly different versions (e.g., with different titles or URLs). The system may retrieve several versions of the same underlying work. The current automated pipeline does not reliably align or distinguish these cases, so human reviewers will need to disambiguate them manually.

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## Core Task Landscape

This paper addresses: **Discrete Geometry of Piecewise-Linear Regions in ReLU Networks**

A total of **50 papers** were analyzed and organized into a taxonomy with **20 categories**.

### Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Geometric Structure and Representation Theory**
- **Computational Methods and Complexity**
- **Expressivity and Capacity Bounds**
- **Approximation Theory and Finite Element Connections**
- **Training Dynamics and Optimization**
- **Applications and Extensions**

### Complete Taxonomy Tree

- Discrete Geometry of Piecewise-Linear Regions in ReLU Networks Survey Taxonomy
- Geometric Structure and Representation Theory
  - Connectivity and Topological Properties ★ (4 papers)
    - [0] Characterizing the Discrete Geometry of ReLU Networks (Anon et al., 2026) [View paper](#)
    - [27] Local and global topological complexity measures of relu neural network functions (Grigsby, 2022) [View paper](#)
    - [36] Accessing the Topological Properties of Neural Network Functions (Masden, 2023) [View paper](#)
    - [38] On transversality of bent hyperplane arrangements and the topological expressiveness of ReLU neural networks (Grigsby, 2022) [View paper](#)
  - Algebraic and Tropical Geometry Frameworks (4 papers)
    - [13] Interpreting neural networks through the polytope lens (Black, 2022) [View paper](#)
    - [24] Tropical geometry of deep neural networks (Liwen Zhang, 2018) [View paper](#)
    - [30] When deep learning meets polyhedral theory: A survey (Huchette, 2023) [View paper](#)
    - [37] Constraining the outputs of ReLU neural networks (Alexandr, 2025) [View paper](#)
  - Piecewise Linear Function Representation (4 papers)
    - [10] Understanding deep neural networks with rectified linear units (Mukherjee, 2016) [View paper](#)
    - [17] Piecewise linear neural networks and deep learning (Tao, 2022) [View paper](#)
    - [44] Stable Parametrization of Continuous and Piecewise-Linear Functions (Goujon, 2022) [View paper](#)
    - [49] Un-rectifying non-linear networks for signal representation (Wen Liang Hwang, 2019) [View paper](#)
- Computational Methods and Complexity
  - Region Enumeration and Traversal Algorithms (4 papers)
    - [12] Traversing the local polytopes of ReLU neural networks (S Xu, 2021) [View paper](#)
    - [18] Algorithmic determination of the combinatorial structure of the linear regions of relu neural networks (Masden, 2025) [View paper](#)
    - [32] Causal Explanations from the Geometric Properties of ReLU Neural Networks (H Woods, 2025) [View paper](#)
    - [46] Discrete Functional Geometry of ReLU Networks via ReLU Transition Graphs (Dhayalkar, 2025) [View paper](#)
  - Computational Complexity Theory (1 papers)
    - [45] The Computational Complexity of Counting Linear Regions in ReLU Neural Networks (Hertrich, 2025) [View paper](#)
  - Empirical Region Analysis (1 papers)
    - [21] Empirical bounds on linear regions of deep rectifier networks (Thiago Serra, 2020) [View paper](#)

- Expressivity and Capacity Bounds
  - Region Count and Complexity Bounds (3 papers)
  - [15] Improved bounds on neural complexity for representing piecewise linear functions (Chen, 2022) [View paper](#)
  - [31] Comparative analysis of the linear regions in ReLU and LeakyReLU networks (Xuan Qi, 2023) [View paper](#)
  - [35] On the number of response regions of deep feed forward networks with piece-wise linear activations (Razvan Pascanu, 2013) [View paper](#)
  - Statistical Learning Bounds (1 papers)
  - [3] Nearly-tight VC-dimension and pseudodimension bounds for piecewise linear neural networks (Bartlett, 2019) [View paper](#)
  - Depth Separation and Expressivity (1 papers)
  - [4] On the depth of monotone ReLU neural networks and ICNNs (Brunck, 2025) [View paper](#)
- Approximation Theory and Finite Element Connections
  - Finite Element Method Connections (3 papers)
  - [6] ReLU deep neural networks and linear finite elements (He, 2018) [View paper](#)
  - [11] Shallow ReLU neural networks and finite elements (Pengzhan Jin, 2024) [View paper](#)
  - [22] 15 Deep learning in high dimension: ReLU neural network expression for (JAA Opschoor, 2022) [View paper](#)
  - Approximation Rate Theory (1 papers)
  - [20] Deep ReLU networks and high-order finite element methods (Joost A. A. Opschoor, 2020) [View paper](#)
  - Spline and Free Knot Approximation (2 papers)
  - [8] Equidistribution-based training of Free Knot Splines and ReLU Neural Networks (Arridge, 2024) [View paper](#)
  - [47] Learning of Continuous and Piecewise-Linear Functions With Hessian Total-Variation Regularization (Daniel, 2022) [View paper](#)
- Training Dynamics and Optimization
  - Local Complexity and Training Dynamics (2 papers)
  - [28] On the Local Complexity of Linear Regions in Deep ReLU Networks (Niket Patel, 2024) [View paper](#)
  - [40] Training Dynamics of Deep Network Linear Regions (Humayun, 2023) [View paper](#)
  - Loss Landscape Geometry (2 papers)
  - [7] Neglected hessian component explains mysteries in sharpness regularization (Atish Agarwala, 2024) [View paper](#)
  - [26] Spurious local minima are common for deep neural networks with piecewise linear activations (Liu Bo, 2022) [View paper](#)
  - Optimization Problem Formulations (2 papers)
  - [5] An analysis of optimization problems involving ReLU neural networks (Hahn, 2025) [View paper](#)
  - [34] The convex landscape of neural networks: Characterizing global optima and stationary points via lasso models (Tolga Ergen, 2025) [View paper](#)
- Applications and Extensions
  - Verification and Control Applications (6 papers)
  - [1] Improved geometric path enumeration for verifying relu neural networks (Stanley Bak, 2020) [View paper](#)
  - [14] A semi-algebraic framework for verification and synthesis of control barrier functions (Andrew Clark, 2024) [View paper](#)
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  - [48] Just-In-Time Piecewise-Linear Semantics for ReLU-type Networks (Duan Hongyi, 2025) [View paper](#)
  - Interpretability and Mechanistic Analysis (1 papers)
  - [9] Polynomial Time Cryptanalytic Extraction of Deep Neural Networks in the Hard-Label Setting (Nicholas Carlini, 2025) [View paper](#)
  - Uncertainty Propagation (1 papers)
  - [2] Piecewise Linear Transformation - Propagating Aleatoric Uncertainty in Neural Networks (Hagn, 2024) [View paper](#)
  - Specialized Architectures and Activation Functions (4 papers)
  - [16] Physics Informed Piecewise Linear Neural Networks for Process Optimization (Koksal, 2023) [View paper](#)
  - [29] PWLU: Learning Specialized Activation Functions With the Piecewise Linear Unit (Zezhou Zhu, 2023) [View paper](#)
  - [42] Deep Learning with S-Shaped Rectified Linear Activation Units (Jin, 2015) [View paper](#)
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  - Domain-Specific Applications (4 papers)
  - [25] Deep learning for biomedical image reconstruction (JC Ye, 2023) [View paper](#)
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  - [39] Cellular automata, many-valued logic, and deep neural networks (Zhang Ya-Ni, 2024) [View paper](#)
  - [41] Equivariant neural networks and piecewise linear representation theory (Gibson, 2024) [View paper](#)

## Narrative

Core task: discrete geometry of piecewise-linear regions in ReLU networks. The field examines how ReLU networks partition input space into polyhedral regions where the function is affine, and how this geometric structure relates to expressivity, complexity, and optimization. The taxonomy organizes work into several main branches. Geometric Structure and Representation Theory investigates the intrinsic properties of these polytopes, including connectivity, topological invariants, and algebraic characterizations—works like Topological Complexity Measures[27] and Bent Hyperplane Transversality[38] explore how activation patterns induce topological features. Computational Methods and Complexity focuses on counting and enumerating linear regions, with foundational contributions such as Response Regions Count[35] and more recent efforts like Counting Linear Regions[45]. Expressivity and Capacity Bounds studies how many regions a network can produce and what functions it can represent, exemplified by VC Dimension Bounds[3] and Neural Complexity Bounds[15]. Approximation Theory connects ReLU networks to classical finite element methods, as seen in ReLU Finite Elements[6] and Deep ReLU Elements[20]. Training Dynamics examines how optimization navigates the piecewise-linear landscape, while Applications extends these ideas to control theory, verification, and interpretability.

Particularly active lines of work contrast theoretical upper bounds on region counts with empirical observations of how networks actually partition space during training. Some studies emphasize the role of depth and width in determining expressivity, while others investigate the connectivity and traversal properties of adjacent regions—Traversing Local Polytopes[12] and Polytope Lens Interpretation[13] illustrate how local geometry informs optimization and interpretability. The original paper, Discrete Geometry ReLU[0], sits within the

Geometric Structure branch, specifically addressing connectivity and topological properties of linear regions. Its emphasis on topological invariants and structural characterization aligns closely with Topological Properties Access[36], which examines how to probe these features computationally, and contrasts with Bent Hyperplane Transversality[38], which focuses on transversality conditions governing region boundaries. This positioning highlights ongoing interest in understanding not just how many regions exist, but how they are organized and interconnected in the input space.

## Related Works in Same Category

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The following **3 sibling papers** share the same taxonomy leaf node with the original paper:

### 1. Local and global topological complexity measures of relu neural network functions

**Authors:** Grigsby, J. Elisenda, Lindsey, Kathryn, Masden, et al. (6 authors total) | **Year/Venue:** 2022 | **URL:** [View paper](#)

#### Abstract

We apply a generalized piecewise-linear (PL) version of Morse theory due to Grunert-Kuhnel-Rote to define and study new local and global notions of topological complexity for fully-connected feedforward ReLU neural network functions,  $F: \mathbb{R}^n \rightarrow \mathbb{R}$ . Along the way, we show how to construct, for each such  $F$ , a canonical polytopal complex  $K(F)$  and a deformation retract of the domain onto  $K(F)$ , yielding a convenient compact model for performing calculations. We also give a construction showing that ...

#### Relationship Analysis

Both papers belong to the Connectivity and Topological Properties category, analyzing structural properties of linear region complexes in ReLU networks. They overlap in studying how polyhedral regions connect and form complexes, with both examining connectivity graphs and topological measures. The original paper focuses on quantitative bounds for connectivity graph properties (average degree, diameter) across network architectures, while the candidate paper develops a theoretical framework using PL Morse theory to define local and global topological complexity measures based on homological properties of sublevel sets.

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### 2. Accessing the Topological Properties of Neural Network Functions

**Authors:** M Masden | **Year/Venue:** 2023 | **URL:** [View paper](#)

#### Abstract

$\hat{\Delta}$  the geometry and  $\hat{\Delta}$  ReLU networks [23], the canonical polyhedral complex of the network, as defined by [10], encodes its decomposition of input space into piecewise linear regions and  $\hat{\Delta}$

#### Relationship Analysis

Both papers belong to the Connectivity and Topological Properties category, focusing on the connectivity graphs and topological structure of linear region complexes in ReLU networks. They share overlapping interests in analyzing how polyhedral regions connect through their faces and in developing computational methods for exploring these structures. The original paper emphasizes theoretical bounds on average degree and diameter of connectivity graphs with empirical validation, while the candidate paper (Masden's dissertation) provides a more foundational categorical framework using sign sequences and duality theory, with algorithms for computing topological invariants like decision boundary topology during training.

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### 3. On transversality of bent hyperplane arrangements and the topological expressiveness of ReLU neural networks

**Authors:** Grigsby, J. Elisenda, J. Elisenda Grigsby, Lindsey, Kathryn, et al. (6 authors total) | **Year/Venue:** 2022 | **URL:** [View paper](#)

#### Abstract

Let  $F: \mathbb{R}^n \rightarrow \mathbb{R}$  be a feedforward ReLU neural network. It is well-known that for any choice of parameters,  $F$  is continuous and piecewise (affine) linear. We lay some foundations for a systematic investigation of how the architecture of  $F$  impacts the geometry and topology of its possible decision regions for binary classification tasks. Following the classical progression for smooth functions in differential topology, we first define the notion of a generic, transversal ReLU neural network and s...

#### Relationship Analysis

Both papers belong to the Connectivity and Topological Properties category, analyzing how polyhedral regions in ReLU networks connect and form complexes. The original paper focuses on quantitative properties of connectivity graphs (average degree bounds, diameter bounds) and their relationship to network architecture, while the candidate paper establishes foundational transversality theory and uses topological methods to prove constraints on decision region topology (e.g., bounded components). The original paper provides graph-theoretic characterizations of region arrangements, whereas the candidate paper develops differential topology frameworks for studying topological expressiveness.

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## Contributions Analysis

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**Overall novelty summary.** The paper contributes new theoretical results on connectivity graphs of linear region complexes in fully-connected ReLU networks, specifically proving that average degree is bounded by twice the input dimension and that diameter has an upper bound independent of input dimension. Within the taxonomy, it resides in the 'Connectivity and Topological Properties' leaf under 'Geometric Structure and Representation Theory', alongside three sibling papers. This leaf represents a moderately populated research direction within a 50-paper taxonomy spanning 20 leaf nodes, indicating focused but not overcrowded attention to connectivity and topological characterization of ReLU region complexes.

The taxonomy reveals that neighboring research directions include 'Algebraic and Tropical Geometry Frameworks' (examining zonotopes and polyhedral theory) and 'Piecewise Linear Function Representation' (studying mathematical properties of continuous piecewise linear functions). The paper's focus on connectivity graphs distinguishes it from these adjacent areas: while algebraic approaches characterize regions through varieties and tropical geometry, this work analyzes how regions connect via shared faces. The scope note for its leaf explicitly excludes local complexity measures and training dynamics, positioning the work as a study of global structural properties rather than optimization-related phenomena or computational enumeration methods covered in other branches.

Among 16 candidates examined across three contributions, the average degree bound shows one refutable candidate from one paper examined, suggesting substantial prior work on this specific result. The diameter bound examined five candidates with none clearly refuting, indicating potentially greater novelty in this direction. The asymptotic characterization contribution examined ten candidates with no refutations, suggesting this aspect may be less directly addressed in prior literature. However, the limited search scope (16 total candidates from top-K semantic search) means these statistics reflect only a narrow slice of potentially relevant work, not an exhaustive survey of connectivity graph analysis in ReLU networks.

Based on the limited literature search covering 16 candidates, the diameter bound and asymptotic characterization appear to offer more novel contributions than the average degree result, which has identifiable prior overlap. The taxonomy structure suggests this work addresses a recognized but not saturated research direction, though the restricted search scope prevents definitive claims about overall novelty across the broader field of ReLU network geometry.

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This paper presents **3 main contributions**, each analyzed against relevant prior work:

## Contribution 1: Upper bound on average degree of connectivity graph

**Description:** The authors prove that for any fully-connected ReLU network, the average number of neighbors (faces) of polyhedral regions in the network's complex is at most  $2d$ , where  $d$  is the input dimension. This bound holds independently of network width and depth.

This contribution was assessed against **1 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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### 1. The Geometry of ReLU Networks through the ReLU Transition Graph

URL: [View paper](#)

#### Prior Art Analysis

ReLU Transition Graph[51] demonstrates that prior work exists on bounding the average degree of ReLU network connectivity graphs. The candidate paper explicitly states it derives 'tight combinatorial bounds on rtg size and diameter' and relates 'average degree of the rtg to generalization error.' The candidate's RTG is structurally identical to the original paper's connectivity graph—both define nodes as linear regions and edges as connections differing by single neuron activations. The candidate's claim to provide 'the first unified treatment of relu network structure via graph theory' and derive bounds on average degree directly challenges the novelty of the original paper's upper bound of  $2d$  on average degree.

#### Evidence

Evidence 1 - **Rationale:** The candidate explicitly claims to derive bounds on average degree of the RTG (which is the same as the connectivity graph). This directly overlaps with the original paper's contribution of bounding average degree at  $2d$ . - **Original:** the average degree of this graph is upper bounded by twice the input dimension regardless of the width and depth of the network - **Candidate:** our contributions include tight combinatorial bounds on rtg size and diameter, a proof of rtg connectivity, and graph-theoretic interpretations of vc-dimension. we also relate entropy and average degree of the rtg to generalization error.

Evidence 2 - **Rationale:** The candidate claims to provide 'the first unified treatment' via graph theory, but the original paper already analyzes the connectivity graph structure. This suggests the candidate represents prior or concurrent work that could refute the original's novelty claim. - **Original:** our analysis builds on the topological perspective of relu network geometry, and follows the same assumptions as masden (2022). our results are best expressed in terms of the complex's connectivity graph(fig.1c), where nodes correspond to polyhedral regions and edges exist between regions that have a... - **Candidate:** this work provides the first unified treatment of relu network structure via graph theory and opens new avenues for compression, regularization, and complexity control rooted in rtg analysis.

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## Contribution 2: Upper bound on connectivity graph diameter independent of input dimension

**Description:** The authors establish that the diameter of the connectivity graph (longest shortest-path distance between any pair of regions) is bounded above by  $(m+1)l$ , where  $m$  is maximum layer width and  $l$  is depth. This bound does not depend on input dimension  $d$ , even though the number of regions grows exponentially with  $d$ .

This contribution was assessed against **5 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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### 1. An improved upper bound on the diameters of subset partition graphs

URL: [View paper](#)

#### Brief Assessment

Subset Partition Diameters[53] analyzes diameter bounds for subset partition graphs (a combinatorial abstraction), not connectivity graphs of ReLU neural network partition complexes. The mathematical structures and proof techniques are fundamentally different.

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### 2. Isometric Path Partition Number of Bridgeless Outerplanar Graphs of Small Diameter

URL: [View paper](#)

#### Brief Assessment

Isometric Path Partition[54] studies graph partitioning problems for outerplanar graphs with specific diameter constraints (2 and 3), which is a completely different mathematical domain from neural network partition complexes and their connectivity properties.

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### 3. A novel modular RBF neural network based on a brain-like partition method

URL: [View paper](#)

#### Brief Assessment

Brain-Like Partition RBF[52] discusses diameter of receptive fields in RBF networks, not connectivity graph diameter bounds in ReLU network partition complexes. These are fundamentally different architectural and geometric concepts.

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### 4. The partition dimension of a graph

URL: [View paper](#)

#### Brief Assessment

Partition Dimension Graph[55] studies partition dimension of general graphs with diameter bounds, not neural network connectivity graphs or ReLU partition complexes. The contexts are fundamentally different mathematical domains.

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### 5. Model selection for minimum-diameter partitioning.

URL: [View paper](#)

#### Brief Assessment

Minimum-Diameter Partitioning[56] focuses on model selection for partitioning problems, not on neural network connectivity graphs or ReLU activation patterns. The candidate addresses a different problem domain.

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## Contribution 3: Characterization of asymptotic behavior and tightness of bounds

**Description:** The authors prove that the average degree increases monotonically as network size grows and that the upper bound of  $2d$  is tight, with the average converging exactly to  $2d$  for shallow networks as the number of neurons approaches infinity. They also establish lower bounds showing every region has at least  $d$  neighbors when the network has at least  $d$  neurons.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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### 1. Local and global topological complexity measures of relu neural network functions

URL: [View paper](#)

#### Brief Assessment

Topological Complexity Measures[27] focuses on topological complexity measures using Morse theory and homological complexity for ReLU networks, not on asymptotic behavior of polyhedral region neighbor bounds or their tightness.

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## 2. Shallow ReLU neural networks and finite elements

URL: [View paper](#)

### Brief Assessment

Shallow ReLU Elements[11] focuses on weak representation of finite element functions via shallow ReLU networks and does not address polyhedral region neighbor bounds or their asymptotic behavior in ReLU network complexes.

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## 3. Traversing the local polytopes of relu neural networks: A unified approach for network verification

URL: [View paper](#)

### Brief Assessment

Unified Network Verification[58] focuses on polytope traversal algorithms for network verification tasks, not on characterizing asymptotic behavior or proving tightness of bounds on polyhedral region neighbor counts in ReLU networks.

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## 4. Robustness Certificates Against Adversarial Examples for ReLU Networks

URL: [View paper](#)

### Brief Assessment

Robustness Certificates ReLU[61] focuses on computing robustness certificates for adversarial examples using the piecewise linear structure of ReLU networks within local polyhedra. It does not address asymptotic behavior of polyhedral region neighbor counts or prove tightness of bounds as network size grows.

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## 5. On the decision boundaries of neural networks: A tropical geometry perspective

URL: [View paper](#)

### Brief Assessment

Tropical Decision Boundaries[57] focuses on characterizing decision boundaries of neural networks through tropical geometry and polytopes, not on analyzing the asymptotic behavior of polyhedral region neighbor bounds in ReLU networks.

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## 6. Optimal Sets and Solution Paths of ReLU Networks

URL: [View paper](#)

### Brief Assessment

Optimal Sets Paths[63] focuses on characterizing optimal solution sets and regularization paths for ReLU networks through convex reformulations, not on asymptotic behavior of polyhedral region neighbor bounds or their tightness as network size grows.

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## 7. Understanding deep neural networks with rectified linear units

URL: [View paper](#)

### Brief Assessment

Understanding Rectified Units[10] focuses on piecewise linear function representation and circuit complexity bounds for ReLU networks, not on polyhedral region connectivity or neighbor bounds in the geometric sense studied by the original paper.

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## 8. Integrating geometries of ReLU feedforward neural networks

URL: [View paper](#)

### Brief Assessment

Integrating ReLU Geometries[59] focuses on binary vector representations and polyhedral decomposition analysis for adversarial detection and network explainability, not on proving asymptotic convergence properties or tightness of neighbor bounds as the original paper does.

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## 9. Topological Signatures of ReLU Neural Network Activation Patterns

URL: [View paper](#)

### Brief Assessment

Topological Activation Signatures[62] focuses on topological signatures of activation patterns using dual graphs and homology, not on asymptotic behavior or tightness of polyhedral region neighbor bounds in ReLU networks.

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## 10. Static analysis of ReLU neural networks with tropical polyhedra

URL: [View paper](#)

### Brief Assessment

Tropical Polyhedra Analysis[60] focuses on static analysis and range estimation for ReLU networks using tropical geometry abstractions, not on characterizing the asymptotic behavior of polyhedral region neighbor bounds or proving tightness results for connectivity graph properties.

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## Appendix: Text Similarity Detection

No high-similarity text segments were detected across any compared papers.

## References

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- [0] Characterizing the Discrete Geometry of ReLU Networks [View paper](#)
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- [60] Static analysis of ReLU neural networks with tropical polyhedra [View paper](#)
- [61] Robustness Certificates Against Adversarial Examples for ReLU Networks [View paper](#)
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