Novelty Assessment Report

Paper: On the Lipschitz Continuity of Set Aggregation Functions and Neural Networks for Sets

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Abstract

The Lipschitz constant of a neural network is connected to several important properties of the network such as its robustness and generalization. It is thus useful in many settings to estimate the Lipschitz constant of a model. Prior work has focused mainly on estimating the Lipschitz constant of multi-layer perceptrons and convolutional neural networks. Here we focus on data modeled as sets or multisets of vectors and on neural networks that can handle such data. These models typically apply some permutation invariant aggregation function, such as the sum, mean or max operator, to the input multisets to produce a single vector for each input sample. In this paper, we investigate whether these aggregation functions, along with an attention-based aggregation function, are Lipschitz continuous with respect to three distance functions for unordered multisets, and we compute their Lipschitz constants. In the general case, we find that each aggregation function is Lipschitz continuous with respect to only one of the three distance functions, while the attention-based function is not Lipschitz continuous with respect to any of them. Then, we build on these results to derive upper bounds on the Lipschitz constant of neural networks that can process multisets of vectors, while we also study their stability to perturbations and generalization under distribution shifts. To empirically verify our theoretical analysis, we conduct a series of experiments on datasets from different domains.

Core Task Landscape

This paper addresses: **Lipschitz Continuity of Neural Networks for Set-Structured Data**

A total of **19 papers** were analyzed and organized into a taxonomy with **13 categories**.

Taxonomy Overview

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

- **Lipschitz Analysis of Set-Aggregation Neural Architectures**
- **Set-Valued Prediction and Classification Methods**
- **Set-Valued Mapping Theory and Applications**
- **Continuous-Depth Model Reachability and Verification**
- **Uncertainty Representation and Robustness Analysis**
- **Specialized Applications of Set-Valued and Lipschitz Methods**

Complete Taxonomy Tree

- Lipschitz Continuity of Neural Networks for Set-Structured Data Survey Taxonomy
- Lipschitz Analysis of Set-Aggregation Neural Architectures
  - Aggregation Function Lipschitz Properties ★ (2 papers)
  - [0] On the Lipschitz Continuity of Set Aggregation Functions and Neural Networks for Sets (Anon et al., 2026) View paper
  - [3] On the limitations of representing functions on sets (Edward Wagstaff, 2019) View paper
  - Complete Network Lipschitz Bounds and Stability (2 papers)
  - [2] Dual Alignment Framework for Few-shot Learning with Inter-Set and Intra-Set Shifts (S Jiang, 2025) View paper
  - [19] Learning RNNs with Commutative State Transitions (Edo Cohen-Karlik, n.d.) View paper
- Set-Valued Prediction and Classification Methods
  - Set-Valued Classifiers with Lipschitz Guarantees (2 papers)
  - [5] Deep generalized prediction set classifier and its theoretical guarantees (Z Wang, 2024) View paper
  - [6] Set-valued classification with out-of-distribution detection for many classes (Z Wang, 2023) View paper
  - Sensitivity Analysis of Neural Network Solution Sets (1 papers)
  - [8] Set-Valued Sensitivity Analysis of Deep Neural Networks (Wang Xin, 2025) View paper
- Set-Valued Mapping Theory and Applications
  - Lipschitz Selection and Existence Criteria (1 papers)
  - [11] Existence Criteria for Lipschitz Selections of Set-Valued Mappings in ${\bf R}^2$ (Shvartsman, 2023) View paper
  - Parametric Set-Valued Equilibrium Problems (1 papers)
  - [10] On Lipschitz continuity of approximate solutions to set-valued equilibrium problems via nonlinear scalarization (L. Q. Anh, 2021) View paper
  - Subdifferential and Coderivative Criteria (1 papers)
  - [9] Lipschitz Properties of Nonsmooth Functions and Set-Valued Mappings via Generalized Differentiation and Applications (Nguyen Mau Nam, 2022) View paper
  - Fuzzy and Stochastic Set-Valued Differential Equations (1 papers)
  - [12] Fuzzy and set-valued stochastic differential equations with local Lipschitz condition (Marek T. Malinowski, 2014) View paper
- Continuous-Depth Model Reachability and Verification
  - Lagrangian Reachtube Construction Methods (2 papers)

    - [14] Robustness analysis of continuous-depth neural networks (Neubauer, 2023) View paper
    - [15] Robustness Analysis of Continuous-Depth Models with Lagrangian Techniques (Sophie A. Neubauer, 2022) View paper
  - Set-Valued Learning and Control Frameworks (1 papers)
    - [13] Set-Valued Methods for Learning, Control and Estimation (Jin, 2023) View paper
- Uncertainty Representation and Robustness Analysis (2 papers)
  - [4] Quantifying aleatoric and epistemic uncertainty: A credal approach (P Hofman, 2024) View paper
  - [7] Formal And Geometric Foundations For Deep Learning Under Safety Constraints (Casadio, 2025) View paper
- Specialized Applications of Set-Valued and Lipschitz Methods
  - Set-Valued Approximation and Operator Theory (2 papers)
  - [16] Universal approximation of set-valued maps and DeepONet approximation of the controllability map (CJ GarcÃ±a-Cervera, n.d.) View paper
  - [18] Inverse Result of Approximation for the Max-Product Neural Network Operators of the Kantorovich Type and Their Saturation Order (Marco Cantarini, 2021) View paper
  - Set-Valued Image Segmentation and PDEs (2 papers)
  - [1] Continuity-preserved deep learning method for solving elliptic interface problems (Jiao Li, 2025) View paper
  - [17] Set-valued maps for image segmentation (Thomas Lorenz, 2001) View paper

Narrative

Core task: Lipschitz continuity of neural networks for set-structured data. This field examines how neural architectures that process sets—collections of elements without inherent order—maintain bounded sensitivity to input perturbations, a property formalized through Lipschitz constants. The taxonomy reveals a landscape organized around several complementary themes. One major branch focuses on the Lipschitz analysis of set-aggregation neural architectures, investigating how permutation-invariant operations like summation or max-pooling propagate continuity guarantees. Another branch addresses set-valued prediction and classification methods, where outputs themselves are sets or intervals rather than point estimates, often motivated by uncertainty quantification. A third branch explores set-valued mapping theory and its applications, drawing on classical analysis to understand multivalued functions in learning contexts. Additional branches examine continuous-depth model reachability and verification, uncertainty representation and robustness analysis, and specialized applications ranging from image segmentation to out-of-distribution detection. Works such as Limitations Functions Sets[3] provide foundational perspectives on aggregation functions, while studies like Credal Uncertainty Quantification[4] and Deep Prediction Set[5] illustrate how set-valued outputs capture epistemic uncertainty.

Particularly active lines of work contrast pointwise Lipschitz bounds for deterministic architectures with set-valued approaches that encode ambiguity or distributional shifts. On one hand, research into aggregation function Lipschitz properties—exemplified by Lipschitz Set Aggregation[0] and closely related to Limitations Functions Sets[3]—seeks tight continuity constants for permutation-invariant layers, enabling certified robustness for graph and point-cloud models. On the other hand, methods like Set-Valued OOD Detection[6] and Deep Prediction Set[5] leverage set-valued outputs to defer decisions under high uncertainty, trading precision for reliability. The original paper, Lipschitz Set Aggregation[0], sits squarely within the aggregation-focused branch, emphasizing rigorous bounds on how set-pooling operations affect network sensitivity. Compared to the more foundational survey in Limitations Functions Sets[3], it offers concrete Lipschitz analysis tailored to modern deep architectures, while differing from uncertainty-driven works like Deep Prediction Set[5] by prioritizing continuity guarantees over probabilistic coverage. This positioning highlights an ongoing tension between deterministic robustness certificates and flexible uncertainty representations across the taxonomy.

Related Works in Same Category

The following **1 sibling papers** share the same taxonomy leaf node with the original paper:

1. On the limitations of representing functions on sets

Authors: Edward Wagstaff, Fabian B. Fuchs, E. Wagstaff, Martin Engelcke, F. Fuchs, et al. (8 authors total) | **Year/Venue**: 2019 | **URL**: View paper

Abstract

Recent work on the representation of functions on sets has considered the use of summation in a latent space to enforce permutation invariance. In particular, it has been conjectured that the dimension of this latent space may remain fixed as the cardinality of the sets under consideration increases. However, we demonstrate that the analysis leading to this conjecture requires mappings which are highly discontinuous and argue that this is only of limited practical use. Motivated by this observat...

Relationship Analysis

Both papers belong to the Aggregation Function Lipschitz Properties category, analyzing theoretical properties of aggregation functions (sum, mean, max) applied to sets or multisets. The original paper focuses on computing Lipschitz constants of these aggregation functions with respect to three specific distance metrics (EMD, Hausdorff, matching distance) and derives upper bounds for neural networks employing these aggregators. The candidate paper instead investigates the representational limitations of sum-decomposition models, proving that a latent dimension at least equal to the maximum set size is necessary for universal function approximation, without directly analyzing Lipschitz continuity properties.

Contributions Analysis

Overall novelty summary. The paper investigates Lipschitz continuity of aggregation functions (sum, mean, max, attention) for neural networks processing set-structured data, deriving Lipschitz constants with respect to three multiset distance functions. It resides in the 'Aggregation Function Lipschitz Properties' leaf, which contains only two papers total. This leaf sits within the broader 'Lipschitz Analysis of Set-Aggregation Neural Architectures' branch, indicating a relatively sparse research direction focused on theoretical properties of permutation-invariant operations rather than end-to-end network analysis.

The taxonomy reveals neighboring work in 'Complete Network Lipschitz Bounds and Stability' (also two papers), which extends aggregation-level analysis to full architectures, and 'Set-Valued Prediction and Classification Methods', which uses Lipschitz theory for uncertainty quantification rather than deterministic continuity. The paper's focus on individual aggregation operators distinguishes it from holistic network verification approaches and from set-valued output methods that encode epistemic uncertainty. Its theoretical lens contrasts with application-driven branches like 'Specialized Applications' covering image segmentation or approximation theory.

Among thirty candidates examined, none clearly refute the three main contributions. For 'Lipschitz continuity analysis of set aggregation functions', ten candidates were reviewed with zero refutable overlaps; similarly, 'Upper bounds on Lipschitz constants' and 'Stability analysis under distribution shifts' each examined ten candidates without identifying prior work that subsumes these results. The sibling paper in the same taxonomy leaf addresses related but distinct aspects of aggregation function limitations. This suggests the specific combination of aggregation operators, distance metrics, and Lipschitz constant derivations may represent a novel synthesis within the limited search scope.

Given the sparse taxonomy leaf (two papers) and absence of refuting candidates among thirty examined, the work appears to occupy a relatively underexplored niche. However, the limited search scale means potentially relevant prior work in broader Lipschitz analysis or set-based learning may exist outside the top-thirty semantic matches. The contribution's novelty hinges on the specific technical framework—particular distance functions and aggregation operators—rather than introducing entirely new problem domains.

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

Contribution 1: Lipschitz continuity analysis of set aggregation functions

Description: The authors analyze whether standard aggregation functions (sum, mean, max) and an attention-based function are Lipschitz continuous with respect to three distance functions for multisets (EMD, Hausdorff distance, matching distance). They compute the Lipschitz constants for each combination and show that each standard aggregation function is Lipschitz continuous with respect to only one distance function in the general case.

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. Pointwise construction of Lipschitz aggregation operators with specific properties

URL: View paper

Brief Assessment

Pointwise Lipschitz Aggregation[35] focuses on constructing aggregation operators from desired values using Lipschitz approximation, not on analyzing whether standard aggregation functions (sum, mean, max) are Lipschitz continuous with respect to specific distance metrics for multisets (EMD, Hausdorff, matching distance).

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2. On Lipschitz properties of generated aggregation functions

URL: View paper

Brief Assessment

Lipschitz Aggregation Properties[33] focuses on generated aggregation functions and their Lipschitz properties, not on analyzing standard aggregation functions (sum, mean, max) with respect to specific multiset distance metrics (EMD, Hausdorff, matching distance) as done in the original paper.

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3. Power-Aggregation of Pseudometrics and the McShane-Whitney Extension Theorem for Lipschitz -Concave Maps

URL: View paper

Brief Assessment

Power-Aggregation Pseudometrics[37] focuses on mathematical theory of pseudometrics and Lipschitz maps in abstract metric spaces, not on neural network aggregation functions or multiset distance metrics.

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4. Algorithmic robust forecast aggregation

URL: View paper

Brief Assessment

Robust Forecast Aggregation[30] focuses on forecast aggregation with information structures and imposes Lipschitz conditions on aggregators in a different context (forecast combination), not on analyzing Lipschitz continuity of standard set aggregation functions (sum, mean, max) with respect to multiset distance metrics.

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5. Aggregation functions: A guide for practitioners

URL: View paper

Brief Assessment

Aggregation Functions Guide[32] is a general practitioner's guide covering broad aggregation functions and mentions Lipschitz constants, but does not provide the specific theoretical analysis of standard aggregation functions (sum, mean, max) with respect to multiset distance metrics (EMD, Hausdorff, matching distance) that forms the core novelty of the original paper.

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6. Complementary Lipschitz continuity results for the distribution of intersections or unions of independent random sets in finite discrete spaces

URL: View paper

Brief Assessment

Complementary Lipschitz Continuity[39] focuses on Lipschitz continuity of intersection/union operations for random set distributions in finite discrete spaces using belief functions, not on neural network aggregation functions with multiset distance metrics.

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7. Modular Quasi-Pseudo Metrics and the Aggregation Problem

URL: View paper

Brief Assessment

Modular Quasi-Pseudo Metrics[36] focuses on aggregating distance metrics themselves (modular quasi-pseudo-metric aggregation functions), not on analyzing Lipschitz continuity of set aggregation functions like sum, mean, and max with respect to distance metrics.

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8. Coherent Upper Conditional Previsions Defined through Conditional Aggregation Operators

URL: View paper

Brief Assessment

Conditional Aggregation Operators[34] focuses on coherent upper conditional previsions constructed through conditional aggregation operators in probability theory, not on Lipschitz continuity analysis of standard set aggregation functions (sum, mean, max) with respect to multiset distance metrics.

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9. Multiple Optimal Solutions and the Best Lipschitz Constants Between an Aggregation Function and Associated Idempotized Aggregation Function

URL: View paper

Brief Assessment

Optimal Lipschitz Constants[38] focuses on Lipschitz constants between aggregation functions and their idempotized versions, not on Lipschitz continuity with respect to distance metrics for multisets (EMD, Hausdorff, matching distance).

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10. On the use of aggregation operations in information fusion processes

URL: View paper

Brief Assessment

Aggregation Information Fusion[31] focuses on general aggregation operations in information fusion contexts (merging uncertain observations, preferences, logical databases) rather than analyzing Lipschitz continuity properties of set aggregation functions with respect to specific distance metrics like EMD, Hausdorff distance, or matching distance.

Contribution 2: Upper bounds on Lipschitz constants of neural networks for sets

Description: The authors derive upper bounds on the Lipschitz constants of neural networks that process multisets by combining their aggregation function analysis with known results for multi-layer perceptrons. They show that networks using mean and max aggregators are Lipschitz continuous with respect to specific metrics, while networks using sum aggregators may not be Lipschitz continuous in general.

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.

1. Is Rewiring Actually Helpful in Graph Neural Networks?

URL: View paper

Brief Assessment

Rewiring Graph Networks[25] focuses on graph neural networks and graph rewiring methods for addressing over-squashing, not on deriving Lipschitz constant bounds for neural networks processing multisets with aggregation functions like sum, mean, and max.

2. Fourier sliced-wasserstein embedding for multisets and measures

URL: View paper

Brief Assessment

Fourier Sliced-Wasserstein Embedding[22] focuses on bi-Lipschitz embeddings for multisets and measures using Fourier transforms of quantile functions, not on deriving upper bounds for Lipschitz constants of neural networks with aggregation functions.

3. On the representation power of set pooling networks

URL: View paper

Brief Assessment

Set Pooling Power[28] focuses on representation power and expressiveness of set pooling networks, not on deriving Lipschitz constant bounds for neural networks processing multisets with specific aggregation functions.

4. Neural-swarm2: Planning and control of heterogeneous multirotor swarms using learned interactions

URL: View paper

Brief Assessment

Neural Swarm Planning[23] focuses on learning aerodynamic interaction forces for multirotor swarms using spectral normalization to ensure Lipschitz continuity, not on deriving theoretical upper bounds for Lipschitz constants of set aggregation neural networks with respect to multiset distance metrics.

5. Neural injective functions for multisets, measures and graphs via a finite witness theorem

URL: View paper

Brief Assessment

Neural Injective Functions[26] focuses on moment injectivity of neural networks for multisets using analytic activations, not on deriving Lipschitz constant bounds for aggregation functions with respect to specific distance metrics.

6. On the HÃ¶lder Stability of Multiset and Graph Neural Networks

URL: View paper

Brief Assessment

Holder Multiset Stability[29] focuses on Hölder stability analysis (a relaxation of Lipschitz continuity) for multiset neural networks, while the original paper derives specific upper bounds on Lipschitz constants by combining aggregation function analysis with MLP results. The technical approaches and metrics differ substantially.

7. A Robust Kernel Statistical Test of Invariance: Detecting Subtle Asymmetries

URL: View paper

Brief Assessment

Kernel Invariance Test[21] focuses on statistical testing of group invariances using kernel methods and probability metrics, not on Lipschitz constant bounds for neural networks processing multisets.

8. On the h\"{o} lder stability of multiset and graph neural networks

URL: View paper

Brief Assessment

Holder Stability Multiset[20] focuses on Hölder stability analysis (a relaxation of Lipschitz continuity) for multiset and graph neural networks, not on deriving upper bounds on Lipschitz constants for set-processing networks as the original paper does.

9. Graph Regression and Classification using Permutation Invariant Representations

URL: View paper

Brief Assessment

Permutation Invariant Regression[24] focuses on graph regression/classification with permutation invariant representations, not on deriving upper bounds for Lipschitz constants of neural networks processing multisets with different aggregation functions.

10. Learning representations of persistence barcodes

URL: View paper

Brief Assessment

Persistence Barcode Representations[27] focuses on learning representations of persistence barcodes (topological summaries) rather than general neural networks for multisets. The paper does not address Lipschitz constant bounds for set aggregation functions or neural networks processing arbitrary multisets.

Contribution 3: Stability and generalization analysis under distribution shifts

Description: The authors analyze the stability of neural networks for sets under input perturbations and relate the Lipschitz constant to generalization performance under distribution shifts. They provide theoretical bounds on output variation under perturbations and connect the Wasserstein distance between distributions to generalization error.

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. Generalizing graph neural networks on out-of-distribution graphs

URL: View paper

Brief Assessment

Generalizing GNN OOD[42] focuses on graph-level tasks with distribution shifts between training and testing graphs, not on set aggregation functions or neural networks for sets as studied in the original paper.

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2. Accuracy on the line: on the strong correlation between out-of-distribution and in-distribution generalization

URL: View paper

Brief Assessment

Accuracy on Line[49] focuses on empirical correlations between in-distribution and out-of-distribution accuracy across various datasets, not on Lipschitz-based stability analysis or theoretical bounds relating Wasserstein distance to generalization error under distribution shifts.

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3. Towards out-of-distribution generalization: A survey

URL: View paper

Brief Assessment

OOD Generalization Survey[47] is a broad survey paper covering various aspects of out-of-distribution generalization. While it discusses stability and generalization under distribution shifts in general terms, it does not present original theoretical analysis of neural network stability with Lipschitz constants or specific bounds on output variation under perturbations as claimed in the original paper's contribution.

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4. Dynamic graph neural networks under spatio-temporal distribution shift

URL: View paper

Brief Assessment

Dynamic GNN Shift[44] focuses on spatio-temporal distribution shifts in dynamic graphs with graph neural networks, not on Lipschitz continuity and stability analysis of neural networks for sets under input perturbations.

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5. An effective baseline for robustness to distributional shift

URL: View paper

Brief Assessment

Effective Robustness Baseline[45] focuses on out-of-distribution detection using an abstention class approach, not on Lipschitz continuity analysis or theoretical bounds on neural network stability under distribution shifts.

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6. Seasoning model soups for robustness to adversarial and natural distribution shifts

URL: View paper

Brief Assessment

Model Soups Robustness[46] focuses on adversarial robustness and distribution shifts in image classification through parameter interpolation, not on Lipschitz continuity analysis or theoretical bounds for neural networks on sets.

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7. Out-of-distribution generalization on graphs: A survey

URL: View paper

Brief Assessment

OOD Generalization Graphs[41] surveys graph-specific distribution shift methods, not general neural network stability analysis. The candidate focuses on graph neural networks under domain shifts, while the original analyzes set aggregation functions and Lipschitz continuity.

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8. Minimax optimal estimation of stability under distribution shift

URL: View paper

Brief Assessment

Minimax Stability Estimation[40] focuses on estimating stability measures for system performance under distribution shifts using KL divergence, not on Lipschitz continuity of neural networks or Wasserstein distance bounds for generalization.

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9. Generalizability of adversarial robustness under distribution shifts

URL: View paper

Brief Assessment

Adversarial Robustness Shifts[43] focuses on adversarial robustness generalization across domains, not on Lipschitz-based stability analysis of set aggregation functions under distribution shifts.

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10. Evaluating model robustness and stability to dataset shift

URL: View paper

Brief Assessment

Model Robustness Evaluation[48] focuses on evaluating model performance under distribution shifts in deployment settings, not on analyzing Lipschitz constants or theoretical stability bounds for neural networks processing sets. The technical approaches and problem formulations differ fundamentally.

Appendix: Text Similarity Detection

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

References

- [0] On the Lipschitz Continuity of Set Aggregation Functions and Neural Networks for Sets View paper
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