Novelty Assessment Report

Paper: Tversky Neural Networks: Psychologically Plausible Deep Learning with Differentiable Tversky Similarity

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Abstract

Work in psychology has highlighted that the geometric model of similarity standard in deep learning is not psychologically plausible because its metric properties such as symmetry do not align with human perception of similarity. In contrast, (Tversky,1977) proposed an axiomatic theory of similarity with psychological plausibility based on a representation of objects as sets of features, and their similarity as a function of their common and distinctive features. This model of similarity has not been used in deep learning before, in part because of the challenge of incorporating discrete set operations. In this paper, we develop a differentiable parameterization of Tversky's similarity that is learnable through gradient descent, and derive basic neural network building blocks such as the \emph{Tversky projection layer}, which unlike the linear projection layer can model non-linear functions such as {\sc xor}. Through experiments with image recognition and language modeling neural networks, we show that the Tversky projection layer is a beneficial replacement for the linear projection layer. For instance, on the NABirds image classification task, a frozen ResNet-50 adapted with a Tversky projection layer achieves a 24.7\% relative accuracy improvement over the linear layer adapter baseline. With Tversky projection layers, GPT-2's perplexity on PTB decreases by 7.8\%, and its parameter count by 34.8\%. Finally, we propose a unified interpretation of both types of projection layers as computing similarities of input stimuli to learned prototypes for which we also propose a novel visualization technique highlighting the interpretability of Tversky projection layers. Our work offers a new paradigm for thinking about the similarity model implicit in modern deep learning, and designing neural networks that are interpretable under an established theory of psychological similarity.

Core Task Landscape

This paper addresses: **Incorporating Psychologically Plausible Similarity Measures into Neural Network Architectures**

A total of **50 papers** were analyzed and organized into a taxonomy with **14 categories**.

Taxonomy Overview

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

- **Psychologically-Grounded Similarity Learning in Neural Networks**
- **Cognitive Similarity in Case-Based and Retrieval Systems**
- **Domain-Specific Applications of Similarity-Based Neural Networks**
- **Theoretical Foundations and Learning Paradigms**

Complete Taxonomy Tree

- Incorporating Psychologically Plausible Similarity Measures into Neural Network Architectures Survey Taxonomy
- Psychologically-Grounded Similarity Learning in Neural Networks
  - Tversky Similarity and Feature-Based Models ★ (1 papers)
  - [0] Tversky Neural Networks: Psychologically Plausible Deep Learning with Differentiable Tversky Similarity (Anon et al., 2026) View paper
  - Human Similarity Judgment Alignment (5 papers)
  - [7] Improving neural network representations using human similarity judgments (Muttenthaler, 2023) View paper
  - [18] Transforming neural network visual representations to predict human judgments of similarity (Attarian, 2020) View paper
  - [33] Embedding Learning for Approximating Person-specific Cognitive Similarity (Cha, n.d.) View paper
  - [42] Adapting Deep Network Features to Capture Psychological Representations (Peterson, 2016) View paper
  - [45] Adapting Deep Network Features to Capture Psychological Representations: An Abridged Report (Joshua C. Peterson, 2017) View paper
  - Psychological Similarity Space Construction (4 papers)
  - [40] Generalizing Psychological Similarity Spaces to Unseen Stimuli: Combining Multidimensional Scaling with Artificial Neural Networks (L Bechberger, 2021) View paper
  - [43] Enriching imagenet with human similarity judgments and psychological embeddings (Brett D. Roads, 2021) View paper
  - [47] Generalizing Psychological Similarity Spaces to Unseen Stimuli (Lucas Bechberger, 2022) View paper
  - [48] Mapping Images to Psychological Similarity Spaces Using Neural Networks (Bechberger, 2022) View paper
  - Cognitive Representation and Conceptual Modeling (7 papers)
  - [4] Conceptual cognitive maps formation with neural successor networks and word embeddings (Paul StÃ¶wer, 2023) View paper
  - [29] Evaluating (and improving) the correspondence between deep neural networks and human representations (Joshua C. Peterson, 2018) View paper
  - [36] Cognitive and psychological computation with neural models (James A. Anderson, 1983) View paper
  - [37] Distinct contributions of functional and deep neural network features to representational similarity of scenes in human brain and behavior (Michelle R. Greene, 2018) View paper
  - [39] Concepts and similarity (Ulrike Hahn, 2013) View paper
  - [46] Grounding semantic cognition using computational modelling and network analysis (Ghose, 2019) View paper

- [50] Categorical perception effects induced by category learning. (Kenneth R. Livingston, 1998) View paper
- Cognitive Similarity in Case-Based and Retrieval Systems
  - Case-Based Reasoning with Neural Similarity (2 papers)
  - [2] Enhancing Case-Based Reasoning with Neural Networks (David B. Leake, 2023) View paper
  - [5] Neural network models for situation similarity assessment in hybrid-CBR (I. Glukhikh, 2023) View paper
  - Cognitive Similarity for Recommendation Systems (4 papers)
  - [11] Cognitive similarity-based collaborative filtering recommendation system (Luong Vuong Nguyen, 2020) View paper
  - [12] A cognitive similarity-based measure to enhance the performance of collaborative filtering-based recommendation system (Gourav Jain, 2022) View paper
  - [17] Double fuzzy clustering driven context neural network optimised with chimp optimisation algorithm for movie rating recommendation system (K. Krishnaveni, 2025) View paper
  - [22] MCSRec: Modeling Cognitive Similarity in Sequential Recommendation with Social Networks (Zhongwang Zhang, 2021) View paper
  - Neural Information Retrieval with Cognitive Similarity (3 papers)
  - [20] Tolerant and adaptive information retrieval with neural networks (Thomas Mandl, 2000) View paper
  - [21] Efficient preprocessing for information retrieval with neural networks (Mandl, 1999) View paper
  - [23] Tolerant information retrieval with backpropagation networks (Thomas Mandl, 2000) View paper
- Domain-Specific Applications of Similarity-Based Neural Networks
  - Medical and Diagnostic Applications (1 papers)
  - [1] Binary Classification of Alzheimer's Disease Using Siamese Neural Network for Early Stage Diagnosis (Ruken Tekin, 2025) View paper
  - Affective and Emotional Computing (4 papers)
  - [6] Brain network manifold learned by cognition-inspired graph embedding model for emotion recognition (Cunbo Li, 2024) View paper
  - [8] Affective neural response generation (Nabiha Asghar, 2018) View paper
  - [25] Emotional Similarity Word Embedding Model for Sentiment Analysis (Kazuyuki Matsumoto, 2022) View paper
  - [41] Fuzzy Contrast Set Based Deep Attention Network for Lexical Analysis and Mental Health Treatment (Usman Ahmed, 2022) View paper
  - Visual and Multimodal Perception (5 papers)
  - [3] Cognitive Fusion of Graph Neural Network and Convolutional Neural Network for Enhanced Hyperspectral Target Detection (Shufang Xu, 2024) View paper
  - [13] Cognitive shape similarity assessment for 3D part search (C. Chu, 2017) View paper
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  - [32] Incorporating human visual properties into neural network models (Jonnalagadda, 2023) View paper
  - [49] Dynamic binding in a neural network for shape recognition. (John E. Hummel, 1992) View paper
  - Semantic and Linguistic Similarity (4 papers)
  - [9] Quantifying the Impact of Predicate Similarities on Knowledge Graph Triple Embeddings. (A Kalinowski, 2022) View paper
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  - [34] Ability of neural network cells in learning teacher motivation scale and prediction of motivation with fuzzy logic system (Zahra Pourtousi, 2021) View paper
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  - [14] Intelligent Processing Technology of Cross Media Intelligence Based on Deep Cognitive Neural Network and Big Data (Mingcan Fang, 2020) View paper
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- Theoretical Foundations and Learning Paradigms (5 papers)
  - [10] Neural Network Meaningful Learning Theory and its Application for Deep Text Clustering (Elnaz Zafarani Moattar, 2024) View paper
  - [24] A Similarity-based Normative Framework for Bio-plausible Neural Nets (Sengupta, 2023) View paper
  - [28] Neural networks with motivation (Shuvaev, 2021) View paper
  - [31] A heuristic computational methodology for structural similarity representation and its applications (Wilbur Peng, 2002) View paper
  - [44] Adaptive structure evolution and biologically plausible synaptic plasticity for recurrent spiking neural networks. (Wenxuan Pan, 2023) View paper

Narrative

Core task: Incorporating psychologically plausible similarity measures into neural network architectures. This field bridges cognitive science and machine learning by embedding human-like notions of similarity—such as feature-based comparisons, asymmetric judgments, and context-dependent weighting—directly into neural models. The taxonomy reveals four main branches: Psychologically-Grounded Similarity Learning focuses on integrating classical cognitive theories (e.g., Tversky's feature-based models) into neural architectures, often drawing on human similarity judgments and psychological embeddings to guide representation learning. Cognitive Similarity in Case-Based and Retrieval Systems adapts these principles for memory-augmented and retrieval-oriented tasks, where similarity drives case selection and analogical reasoning. Domain-Specific Applications demonstrate how psychologically informed similarity can enhance performance in areas ranging from medical diagnosis to recommendation systems, while Theoretical Foundations and Learning Paradigms explore the underlying computational principles, including biologically plausible learning rules and developmental cognitive architectures.

Recent work highlights a tension between faithfully modeling human similarity and achieving robust generalization in neural systems. Studies like Human Similarity Judgments[7] and Psychological Similarity Mapping[48] emphasize capturing fine-grained human perceptual structure, while others such as Generalizing Similarity Spaces[40] and ImageNet Psychological Embeddings[43] investigate how well these embeddings transfer across tasks. Tversky Neural Networks[0] sits squarely within the Psychologically-Grounded branch, explicitly incorporating Tversky's asymmetric, feature-based similarity framework into neural computation. This contrasts with approaches like Neural CBR Enhancement[2] and Hybrid CBR Similarity[5], which prioritize retrieval efficiency and case adaptation over strict adherence to cognitive theory. The original work's emphasis on feature-level psychological plausibility positions it as a foundational contribution, offering a principled alternative to purely data-driven similarity metrics while raising questions about scalability and domain adaptation.

Related Works in Same Category

No sibling papers were found in the same taxonomy leaf. A taxonomy-subtopic-level comparison will be produced instead.

Taxonomy-Level Summary

Sibling Subtopics

- **Cognitive Representation and Conceptual Modeling** (leaves: 1, papers: 7)
- Scope: Neural architectures modeling cognitive structures such as conceptual spaces, cognitive maps, or semantic representations informed by psychological theory.
- Exclude: Excludes purely data-driven semantic models or applications without explicit cognitive grounding; see domain applications.
- **Human Similarity Judgment Alignment** (leaves: 1, papers: 5)
- Scope: Methods that align neural network representations with human similarity judgments through supervision, transformation, or embedding learning.
- Exclude: Excludes unsupervised representation learning or models not validated against human judgments; see cognitive representation modeling.
- **Psychological Similarity Space Construction** (leaves: 1, papers: 4)
- Scope: Techniques for mapping stimuli into low-dimensional psychological similarity spaces using neural networks combined with multidimensional scaling or human ratings.
- Exclude: Excludes purely algorithmic MDS or spaces not derived from psychological data; see representation learning without human grounding.

Contributions Analysis

Overall novelty summary. The paper develops a differentiable parameterization of Tversky's feature-based similarity theory and introduces the Tversky projection layer as a neural network building block. According to the taxonomy, this work occupies the 'Tversky Similarity and Feature-Based Models' leaf, which contains only this paper—indicating a sparse research direction within the broader field of psychologically-grounded similarity learning. The taxonomy shows 50 papers across 14 leaf nodes, with sibling leaves like 'Human Similarity Judgment Alignment' (5 papers) and 'Psychological Similarity Space Construction' (4 papers) representing more populated adjacent areas.

The taxonomy structure reveals that most related work clusters in neighboring leaves focused on aligning neural representations with human judgments or constructing psychological similarity spaces through multidimensional scaling. The 'Cognitive Representation and Conceptual Modeling' leaf (7 papers) addresses broader cognitive structures, while 'Case-Based Reasoning with Neural Similarity' (2 papers) applies similarity learning to retrieval tasks. The original paper's leaf explicitly excludes geometric similarity models and approaches not grounded in psychological feature theories, positioning it as a foundational architectural contribution rather than an application-oriented or judgment-alignment method.

Among 25 candidates examined, the first contribution (differentiable Tversky parameterization) shows one refutable candidate from 5 examined, suggesting some prior exploration of making Tversky similarity differentiable. The second contribution (Tversky projection layer) examined 10 candidates with none clearly refuting it, indicating relative novelty in architectural integration. The third contribution (unified interpretation framework) also examined 10 candidates without clear refutation. The limited search scope means these statistics reflect top-K semantic matches rather than exhaustive coverage, and the single refutable finding for the core parameterization warrants attention to how the implementation differs from prior attempts.

Based on the limited 25-candidate search, the architectural contributions appear more novel than the core differentiability mechanism. The taxonomy's sparse population of the Tversky-specific leaf suggests this direction has received minimal prior attention, though the single refutable candidate indicates the fundamental idea may have precedent. The analysis captures semantic neighbors but cannot rule out relevant work in adjacent cognitive science or optimization literature outside the search scope.

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

Contribution 1: Differentiable parameterization of Tversky similarity for gradient-based learning

Description: The authors propose a novel differentiable formulation of Tversky's feature-based similarity function by representing features as vectors and objects dually as both vectors and sets. This enables the incorporation of Tversky's psychologically plausible similarity model into neural networks trained with gradient descent, addressing the challenge of differentiating through discrete set operations.

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. Ensemble of Tversky-Indexed Graph Neural Network and CNN for Plant Leaf Disease Prediction

URL: View paper

Brief Assessment

Tversky Plant Disease[62] applies Tversky similarity in a graph neural network context for plant disease classification, but does not propose a differentiable parameterization of Tversky's feature-based similarity function for gradient-based learning in the manner described by the original paper.

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2. Automatic Traffic Sign Detection and Recognition Using SegU-Net and a Modified Tversky Loss Function With L1-Constraint

URL: View paper

Brief Assessment

Tversky Traffic Signs[61] applies the Tversky loss function to image segmentation for traffic sign detection, not the development of a differentiable parameterization of Tversky's similarity theory for neural network learning. The candidate uses Tversky loss as an existing technique rather than proposing its differentiable formulation.

3. Psychologically Plausible Deep Learning

URL: View paper

Prior Art Analysis

Psychologically Plausible Learning[65] demonstrates that prior work exists on developing differentiable parameterizations of Tversky similarity for gradient-based learning. The candidate explicitly states they 'developed the first differentiable parameterization of tversky similarity' and describes the same technical approach: representing features as vectors, objects dually as vectors and sets, and enabling gradient-based optimization. Both papers address the identical challenge of making Tversky's non-differentiable set operations compatible with gradient descent, propose the same core architectural components (Tversky similarity and projection layers), and demonstrate applications in neural networks. The candidate's work predates or coincides with the original submission timeline, establishing prior art on this specific contribution.

Evidence

Evidence 1 - **Rationale**: Both papers claim to be the first to develop a differentiable parameterization of Tversky similarity. The candidate explicitly states 'i developed the first differentiable parameterization' using the same technical approach and resulting in the same architectural components (Tversky similarity and projection layers), directly challenging the original's novelty claim. - **Original**: to address this gap, we propose a novel representation of features as vectors of the same dimensionality as object vectors, and a dual representation of objects both as vectors and as sets, such that an object is the set of features with which it has a positive dot product. this representation of ob... - **Candidate**: i developed the first differentiable parameterization of tversky similarity that enables gradient-based optimization while preserving psychological plausibility. this breakthrough led to two novel architectural components: the tversky similarity layer and the tversky projection layer, which can repl...

Evidence 2 - **Rationale**: Both papers identify the identical technical challenge: Tversky's non-differentiable set operations prevent integration with gradient-based learning. This shows they are addressing the exact same problem space and technical barrier. - **Original**: the formulation of a differentiable tversky similarity function is non-trivial because it employs measures of set intersections and differences, which are not differentiable with respect to object features comprising those sets. - **Candidate**: tversky's feature-matching theory offers a psychologically grounded alternative: objects are represented as sets of features, and their similarity is computed as a weighted combination of common and distinctive features. despite its success in psychology, this model's non-differentiable set operatio...

Evidence 3 - **Rationale**: Both papers propose the same architectural component (Tversky projection layer) as a replacement for standard neural network layers, demonstrating identical technical contributions. - **Original**: we propose the tversky projection neural layer, which is analogous to the linear projection layer but is based on tversky's model of similarity. - **Candidate**: this breakthrough led to two novel architectural components: the tversky similarity layer and the tversky projection layer, which can replace standard geometric similarity and multi-layer perceptron modules throughout deep networks.

Evidence 4 - **Rationale**: The original paper's detailed technical approach (dual representation using dot products) is claimed as a novel contribution, but the candidate states they developed this same differentiable parameterization first, establishing prior work on this specific technical innovation. - **Original**: dual representation of objects as vectors and as sets: given the learnable finite universe ω of features vectors fk ∈ rd, and an object represented as the vector x ∈ rd, we propose x · fk to be the scalar measure of feature fk in x, and a second representation of x as the set x = {fk ∈ ω|x·fk > 0} of... - **Candidate**: i developed the first differentiable parameterization of tversky similarity, enabling gradient-based learning while preserving psychological plausibility.

4. Automatic Thyroid Ultrasound Image Segmentation Based on U-shaped Network

URL: View paper

Brief Assessment

Thyroid Ultrasound Segmentation[63] uses Tversky loss as a segmentation objective function for medical imaging, not as a differentiable similarity measure for neural network architectures. The candidate does not address the core novelty of representing objects dually as vectors and sets to enable gradient-based learning of Tversky similarity.

5. Ranking Aware Loss for CNNâBased Chagas Disease Detection from ECGs

URL: View paper

Brief Assessment

Chagas Ranking Loss[64] applies Tversky concepts to loss function design for ranking tasks in medical imaging, not to developing a differentiable parameterization of Tversky similarity for general neural network architectures. The candidate focuses on ranking-aware optimization for ECG classification rather than the fundamental problem of making Tversky's feature-based similarity differentiable for gradient descent.

Contribution 2: Tversky projection layer as a neural network building block

Description: The authors introduce the Tversky projection layer, a neural network module analogous to the linear projection layer but based on Tversky similarity. This layer can model non-linear functions like XOR that linear layers cannot, and serves as a replacement for standard projection layers in deep learning architectures.

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. Solving XOR in Spike Neural Network (SNN) with Component-off-the-Shelf

URL: View paper

Brief Assessment

Spike XOR Network[56] focuses on implementing XOR using spiking neural networks with hardware components (LIF neurons, filters, operational amplifiers), not on developing similarity-based projection layers for deep learning architectures.

2. MA-GRNN: a high-efficient modeling attack approach utilizing generalized regression neural network for XOR arbiter physical unclonable functions

URL: View paper

Brief Assessment

GRNN PUF Attack[54] focuses on modeling attacks against XOR arbiter physical unclonable functions using generalized regression neural networks for security applications, not on developing psychologically plausible neural network layers based on Tversky similarity theory.

3. Learning in memristive neural network architectures using analog backpropagation circuits

URL: View paper

Brief Assessment

Memristive Analog Backpropagation[59] focuses on analog circuit implementations of backpropagation learning in memristive crossbar arrays for various neural network architectures. It does not address similarity-based projection layers or non-linear function modeling through similarity measures like the Tversky projection layer.

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4. Transformer learning-based neural network algorithms for identification and detection of electronic bullying in social media

URL: View paper

Brief Assessment

Cyberbullying Detection Transformer[52] focuses on cyberbullying detection using standard transformer architectures (XLM-RoBERTa) and CNN-BiLSTM models with word2vec embeddings. It does not propose novel neural network layers or similarity-based projection mechanisms that would challenge the novelty of the Tversky projection layer.

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5. Modeling non-linear communication systems using neural networks

URL: View paper

Brief Assessment

Neural Nonlinear Communication[57] focuses on modeling nonlinear communication systems using neural networks for Hammerstein systems, not on developing similarity-based projection layers as building blocks for deep learning architectures.

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6. Research on Perceptron Neural Network Based on Memristor

URL: View paper

Brief Assessment

Memristor Perceptron Network[55] focuses on hardware implementation of perceptron networks using memristors for XOR and classification tasks, not on similarity-based projection layers or Tversky similarity theory.

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7. PReLU: Yet Another Single-Layer Solution to the XOR Problem

URL: View paper

Brief Assessment

PReLU XOR Solution[53] focuses on using PReLU activation in single-layer networks for XOR, not on similarity-based projection layers or Tversky's psychological theory of similarity.

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8. Efficient compilation and mapping of fixed function combinational logic onto digital signal processors targeting neural network inference and utilizing high-level â¦

URL: View paper

Brief Assessment

Combinational Logic Compilation[60] focuses on compiling fixed function combinational logic (AND, OR, XOR operations) onto digital signal processors for neural network inference. This is fundamentally different from the Tversky projection layer, which is a learnable neural network module based on psychological similarity theory that can model non-linear functions through gradient descent training.

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9. Artificial neural networks for modelling and control of non-linear systems

URL: View paper

Brief Assessment

Neural Nonlinear Control[58] focuses on neural network control systems and mentions XOR as a historical limitation of early models, not as a contribution involving similarity-based projection layers or Tversky theory.

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10. Deep fuzzy hashing network for efficient image retrieval

URL: View paper

Brief Assessment

Deep Fuzzy Hashing[51] focuses on fuzzy logic-based hashing for image retrieval using XOR operations in convolutional and fully connected layers, not on similarity-based projection layers as general neural network building blocks for modeling non-linear functions.

Contribution 3: Unified interpretation framework and visualization technique for projection layers

Description: The authors present a unified framework interpreting both linear and Tversky projection layers as computing similarities between inputs and learned prototypes. They introduce a novel visualization method that specifies projection parameters in the data domain, enabling human-interpretable visualization of learned prototypes and features.

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. Interpretable optical network fault detection and localization with multi-task graph prototype learning

URL: View paper

Brief Assessment

Graph Prototype Fault[67] focuses on interpretable fault detection in optical networks using graph neural networks and prototype learning for network topology analysis. This is fundamentally different from the original paper's framework for interpreting linear and Tversky projection layers in deep learning architectures through similarity computations and data-domain visualization.

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2. PatchCT: Aligning Patch Set and Label Set with Conditional Transport for Multi-Label Image Classification

URL: View paper

Brief Assessment

PatchCT Multi-Label[72] focuses on multi-label image classification using conditional transport theory to align visual patches and textual labels. It does not address interpretation of projection layers as similarity computations to learned prototypes, which is the core contribution of the original paper.

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3. Class Incremental Learning for Character String Recognition

URL: View paper

Brief Assessment

Incremental Character Recognition[69] focuses on class incremental learning for character recognition using linear projection layers, not on interpreting projection layers as similarity computations or developing visualization techniques for learned prototypes and features.

4. Align2Concept: Language Guided Interpretable Image Recognition by Visual Prototype and Textual Concept Alignment

URL: View paper

Brief Assessment

Align2Concept Visual Textual[70] focuses on aligning visual prototypes with textual concepts for interpretable image recognition, not on interpreting projection layers as similarity computations or visualizing projection parameters in the data domain.

5. Example or prototype? learning concept-based explanations in time-series

URL: View paper

Brief Assessment

Example or Prototype[73] focuses on concept-based explanations for time-series classification using autoencoders and prototypes, not on interpreting projection layers as similarity computations. The candidate addresses XAI methods for explaining classifier decisions to end-users, while the original work develops a novel neural network architecture based on Tversky similarity theory.

6. ProtoSteer: Steering deep sequence model with prototypes

URL: View paper

Brief Assessment

ProtoSteer Sequence Model[75] focuses on steering deep sequence models through interactive prototype editing for tasks like sentiment analysis and diagnostics. It does not address the interpretation of projection layers as similarity computations or propose visualization techniques for projection layer parameters in the data domain.

7. This looks like those: Illuminating prototypical concepts using multiple visualizations

URL: View paper

Brief Assessment

Prototypical Concepts Visualization[66] focuses on visualizing prototypical concepts in image classification networks using multiple training image patches, not on interpreting projection layers as similarity computations or providing a unified framework for linear and Tversky projections.

8. Deep learning for case-based reasoning through prototypes: A neural network that explains its predictions

URL: View paper

Brief Assessment

Prototypes CBR Explanation[68] focuses on case-based reasoning through prototypes in autoencoders for classification tasks, not on interpreting projection layers as similarity computations. The candidate's visualization method decodes prototype vectors through a decoder network, while the original paper proposes data-domain specification of projection parameters for both linear and Tversky layers.

9. This looks like that, because... explaining prototypes for interpretable image recognition

URL: View paper

Brief Assessment

This Looks Like[71] focuses on explaining visual prototypes in image recognition models (specifically ProtoPNet) by quantifying importance of visual characteristics (hue, shape, texture, etc.). The original paper proposes interpreting projection layers as similarity computations in deep learning architectures with a novel data-domain visualization method. These are fundamentally different contributions addressing different problems in different domains.

10. Attribute Prototype Network for Any-Shot Learning

URL: View paper

Brief Assessment

Attribute Prototype Network[74] focuses on learning attribute prototypes for any-shot learning in computer vision, not on interpreting projection layers as similarity computations. The visualization methods serve different purposes - APN visualizes learned attribute prototypes for localization, while the original paper proposes a general framework for interpreting projection layer parameters.

Appendix: Text Similarity Detection

Textual similarity detection checked 25 papers and found 1 similarity segment(s) across 1 paper(s).

The following **1 paper(s)** were detected to have high textual similarity with the original paper. These may represent different versions of the same work, duplicate submissions, or papers with substantial textual overlap. Readers are advised to verify these relationships independently.

1. Psychologically Plausible Deep Learning

Detected in: Contribution: contribution_1

⚠ **Note**: This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

References

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