Novelty Assessment Report

Paper: Learning Adaptive Distribution Alignment with Neural Characteristic Function for Graph Domain Adaptation
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Abstract

Graph Domain Adaptation (GDA) transfers knowledge from labeled source graphs to unlabeled target graphs but is challenged by complex, multi-faceted distributional shifts. Existing methods attempt to reduce distributional shifts by aligning manually selected graph elements (e.g., node attributes or structural statistics), which typically require manually designed graph filters to extract relevant features before alignment. However, such approaches are inflexible: they rely on scenario-specific heuristics, and struggle when dominant discrepancies vary across transfer scenarios. To address these limitations, we propose \textbf{ADAlign}, an Adaptive Distribution Alignment framework for GDA. Unlike heuristic methods, ADAlign requires no manual specification of alignment criteria. It automatically identifies the most relevant discrepancies in each transfer and aligns them jointly, capturing the interplay between attributes, structures, and their dependencies. This makes ADAlign flexible, scenario-aware, and robust to diverse and dynamically evolving shifts. To enable this adaptivity, we introduce the Neural Spectral Discrepancy (NSD), a theoretically principled parametric distance that provides a unified view of cross-graph shifts. NSD leverages neural characteristic function in the spectral domain to encode feature-structure dependencies of all orders, while a learnable frequency sampler adaptively emphasizes the most informative spectral components for each task via minimax paradigm. Extensive experiments on 10 datasets and 16 transfer tasks show that ADAlign not only outperforms state-of-the-art baselines but also achieves efficiency gains with lower memory usage and faster training.

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.

If you have any questions, please contact: mingzhang23@m.fudan.edu.cn

Core Task Landscape

This paper addresses: **graph domain adaptation with distributional shift alignment**

A total of **50 papers** were analyzed and organized into a taxonomy with **31 categories**.

Taxonomy Overview

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

- **Alignment Mechanism and Optimization Strategy**
- **Problem Setting and Transfer Scenario**
- **Out-of-Distribution Generalization and Invariance Learning**
- **Graph-Relational and Multi-Domain Topology Modeling**
- **Application-Specific Graph Domain Adaptation**
- **Benchmarking, Evaluation, and Survey Studies**

Complete Taxonomy Tree

- graph domain adaptation with distributional shift alignment Survey Taxonomy
- Alignment Mechanism and Optimization Strategy
  - Adversarial Domain Alignment
  - Feature-Level Adversarial Alignment (2 papers)
    - [3] Graph transfer learning via adversarial domain adaptation with graph convolution (Quanyu Dai, 2022) View paper
    - [36] Gcan: Graph convolutional adversarial network for unsupervised domain adaptation (Xinhong Ma, 2019) View paper
  - Joint Feature-Structure Adversarial Alignment (1 papers)
    - [8] Joint domain adaptive graph convolutional network (Ting Zhe, 2024) View paper
  - Optimal Transport and Metric-Based Alignment
  - Optimal Transport for Graph Alignment (2 papers)
    - [4] Gradual domain adaptation for graph learning (Chen Xi-ming, 2025) View paper
    - [18] GNN Domain Adaptation using Optimal Transport (Q Zhu, 2023) View paper
  - Maximum Mean Discrepancy and Kernel-Based Alignment (2 papers)
    - [28] Structural domain adaptation with latent graph alignment (Yue Zhang, 2018) View paper
    - [38] A graph embedding framework for maximum mean discrepancy-based domain adaptation algorithms (Yiming Chen, 2019) View paper
  - Spectral and Graph-Theoretic Alignment
  - Spectral Regularization and Basis Alignment (3 papers)
    - [32] SPA: A graph spectral alignment perspective for domain adaptation (Xiao Zhiqing, 2023) View paper
    - [48] Domain adaptation on graphs by learning aligned graph bases (Pilanci, 2020) View paper
    - [49] Graph domain adaptation via theory-grounded spectral regularization (Y You, 2023) View paper
  - Adaptive Spectral Discrepancy Alignment ★ (1 papers)
    - [0] Learning Adaptive Distribution Alignment with Neural Characteristic Function for Graph Domain Adaptation (Anon et al., 2026) View paper
  - Prototype and Instance-Level Alignment

- Prototype-Anchored Alignment (2 papers)
  - [5] PALA: Class-imbalanced graph domain adaptation via prototype-anchored learning and alignment (Xin Ma, 2025) View paper
  - [20] Cross-domain detection via graph-induced prototype alignment (Minghao Xu, 2020) View paper
- Instance-Level Contrastive Alignment (2 papers)
  - [9] Fine-Grained Graph Domain Adaptation via Instance Contrastive Learning (Shengyue Liu, 2025) View paper
  - [42] NI-UDA: Graph contrastive domain adaptation for nonshared-and-imbalanced unsupervised domain adaptation (Guangyi Xiao, 2022) View paper
- Graph Structure Augmentation and Smoothness Regularization
- Link Prediction and Structure Bridging (1 papers)
  - [1] Bridging source and target domains via link prediction for unsupervised domain adaptation on graphs (Yilong Wang, 2025) View paper
- Smoothness and Structural Regularization (2 papers)
  - [25] Smoothness really matters: A simple yet effective approach for unsupervised graph domain adaptation (Chen Wei, 2025) View paper
  - [43] TFGDA: Exploring topology and feature alignment in semi-supervised graph domain adaptation through robust clustering (Jun Dan, 2024) View paper

- Problem Setting and Transfer Scenario
  - Source-Free and Privacy-Preserving Adaptation
  - Source-Free Graph Domain Adaptation (1 papers)
    - [6] Source free graph unsupervised domain adaptation (Haitao Mao, 2024) View paper
  - Diffusion-Based Source-Free Adaptation (1 papers)
    - [37] Gala: Graph diffusion-based alignment with jigsaw for source-free domain adaptation (JunYu Luo, 2024) View paper
  - Semi-Supervised and Partially Labeled Adaptation (1 papers)
  - [16] Semi-supervised domain adaptation in graph transfer learning (Ziyue Qiao, 2023) View paper
  - Gradual and Multi-Step Domain Adaptation (1 papers)
  - [10] Gradual domain adaptation: Theory and algorithms (He Yifei, 2024) View paper
  - Multi-Source and Heterogeneous Domain Adaptation
  - Multi-Source Graph Domain Adaptation (1 papers)
    - [17] Transfer graph feature alignment guided multi-source domain adaptation network for machinery fault diagnosis (Zhengwu Liu, 2024) View paper
  - Heterogeneous Feature Space Alignment (1 papers)
    - [11] Heterogeneous domain adaptation for IoT intrusion detection: A geometric graph alignment approach (Jiashu Wu, 2023) View paper
  - Open-Set and Non-Shared Class Adaptation (2 papers)
  - [31] Progressive graph learning for open-set domain adaptation (Yadan Luo, 2020) View paper
  - [40] Cross-domain graph level anomaly detection (Zhong Li, 2024) View paper
  - Test-Time and Online Adaptation
  - Test-Time Graph Adaptation (1 papers)
    - [30] Test-time adaptation on recommender system with data-centric graph transformation (Ya-ting Liu, 2025) View paper
  - Continual and Evolving Domain Adaptation (2 papers)
    - [41] Gcal: Adapting graph models to evolving domain shifts (Qiao, 2025) View paper
    - [47] Online gnn evaluation under test-time graph distribution shifts (Zheng Xin, 2024) View paper
- Out-of-Distribution Generalization and Invariance Learning
  - Causal Invariance and Intervention-Based Methods (3 papers)
  - [2] Learning causally invariant representations for out-of-distribution generalization on graphs (Chen Yongqiang, 2022) View paper
  - [21] Graph out-of-distribution generalization via causal intervention (Qitian Wu, 2024) View paper
  - [33] Invariance principle meets out-of-distribution generalization on graphs (Y Chen, 2022) View paper
  - Data Augmentation and Extrapolation for OOD Generalization (3 papers)
  - [29] Graph out-of-distribution generalization with controllable data augmentation (Bin Lu, 2024) View paper
  - [35] Graph structure extrapolation for out-of-distribution generalization (X Li, 2024) View paper
  - [50] Graph structure and feature extrapolation for out-of-distribution generalization (Li, 2023) View paper
  - Mixture-of-Experts and Multi-Environment Modeling (2 papers)
  - [19] GraphMETRO: Mitigating Complex Graph Distribution Shifts via Mixture of Aligned Experts (Kaidi Cao, 2024) View paper
  - [44] GraphSHINE: Training Shift-Robust Graph Neural Networks with Environment Inference (Q Wu, 2024) View paper
  - Heterophilic and Structural Shift Robustness (1 papers)
  - [23] Leveraging invariant principle for heterophilic graph structure distribution shifts (Jinluan Yang, 2025) View paper
- Graph-Relational and Multi-Domain Topology Modeling (1 papers)
  - [13] Graph-relational domain adaptation (Xu Zihao, 2022) View paper
- Application-Specific Graph Domain Adaptation
  - Person Re-Identification and Visual Recognition (2 papers)
  - [24] Graph-based local feature adaptation for cross-domain person re-identification (Jun Wang, 2022) View paper
  - [27] Unsupervised domain adaptation for person re-identification via heterogeneous graph alignment (Minying Zhang, 2021) View paper
  - Medical Image Analysis and Survival Prediction (1 papers)
  - [12] Graph domain adaptation with dual-branch encoder and two-level alignment for whole slide image-based survival prediction (Shou, 2025) View paper
  - Fault Diagnosis and Industrial Monitoring (2 papers)
  - [26] Multichannel domain adaptation graph convolutional networks-based fault diagnosis method and with its application (Zhiwen Chen, 2022) View paper
  - [45] An adaptive multihop branch ensemble-based Graph Adaptation Framework with edge-cloud orchestration for condition monitoring (Bufan Liu, 2023) View paper
  - Remote Sensing and Hyperspectral Image Classification (1 papers)

    - [46] Joint correlation alignment-based graph neural network for domain adaptation of multitemporal hyperspectral remote sensing images (Wenjin Wang, 2021) View paper
    - Multivariate Time-Series and Sensor Networks (1 papers)
    - [39] Sea++: Multi-graph-based higher-order sensor alignment for multivariate time-series unsupervised domain adaptation (Yucheng Wang, 2024) View paper
- Benchmarking, Evaluation, and Survey Studies
    - Comprehensive Surveys and Taxonomies (3 papers)
    - [7] Beyond generalization: A survey of out-of-distribution adaptation on graphs (Liu ShuHan, 2024) View paper
    - [14] Graph learning under distribution shifts: A comprehensive survey on domain adaptation, out-of-distribution, and continual learning (Wu Man, 2024) View paper
    - [15] A survey of deep graph learning under distribution shifts: from graph out-of-distribution generalization to adaptation (Zhang Ke-xin, 2024) View paper
    - Benchmarking and Empirical Evaluation Frameworks (2 papers)
    - [22] Model-Free Graph Data Selection under Distribution Shift (TW Li, 2025) View paper
    - [34] Revisiting, benchmarking and understanding unsupervised graph domain adaptation (Liu Meihan, 2024) View paper

Narrative

Core task: graph domain adaptation with distributional shift alignment. This field addresses the challenge of transferring graph neural network models across domains where node features, graph structures, or label distributions differ substantially. The taxonomy organizes research into several main branches. Alignment Mechanism and Optimization Strategy encompasses methods that explicitly reduce domain discrepancies through adversarial training, optimal transport, or spectral techniques. Problem Setting and Transfer Scenario distinguishes works by the availability of labels (unsupervised, semi-supervised) and the nature of domain shifts (e.g., source-free adaptation, gradual domain shifts). Out-of-Distribution Generalization and Invariance Learning focuses on learning representations that remain stable under distributional changes, often by identifying causal or invariant substructures. Graph-Relational and Multi-Domain Topology Modeling tackles scenarios where graph connectivity itself varies across domains or multiple related domains must be handled jointly. Application-Specific Graph Domain Adaptation tailors methods to concrete tasks such as recommendation systems, anomaly detection, or molecular property prediction, while Benchmarking, Evaluation, and Survey Studies provide standardized datasets and comparative analyses to guide the field.

Several active lines of work reveal key trade-offs and open questions. Many studies pursue explicit alignment of feature or structural distributions using adversarial or metric-based objectives, as seen in works like Bridging source and target[1] and PALA[5], yet these approaches can struggle when domain gaps are large or when source data is unavailable, motivating source-free methods such as Source free graph unsupervised[6]. Another prominent direction emphasizes invariance learning, where methods like Learning causally invariant representations[2] and Graph transfer learning via[3] aim to extract domain-agnostic subgraphs or causal mechanisms, trading off simplicity for robustness. Learning Adaptive Distribution Alignment[0] sits within the spectral alignment cluster, proposing adaptive mechanisms to handle varying spectral discrepancies across domains. Compared to neighboring works that rely on fixed alignment criteria, it emphasizes dynamic adjustment of alignment strength, positioning it as a flexible alternative to more rigid spectral or adversarial strategies while sharing the broader goal of mitigating distributional shifts through principled graph-theoretic tools.

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

Both subtopics address spectral approaches to graph domain adaptation, leveraging frequency-domain representations to align distributions across graphs. The original leaf focuses specifically on adaptive or learnable spectral discrepancy measures that automatically identify relevant frequency components, while the sibling category emphasizes learning or matching spectral bases and eigenspaces themselves. The key distinction lies in whether the method adapts the discrepancy measure (original) versus aligning the spectral representations directly (sibling).

Similarities: - Both operate in the spectral/frequency domain of graph signals - Both aim to align distributional shifts across graph domains - Both go beyond using spectral features merely as static input - Both involve learning components rather than using fixed spectral transformations

Differences: - Original leaf: Focuses on adaptive discrepancy measures that learn which frequency components matter for alignment - Sibling: Focuses on learning or matching the spectral bases/eigenspaces themselves - Original leaf: The adaptation mechanism targets the measurement of spectral differences - Sibling: The adaptation mechanism targets the spectral representation spaces - Original leaf: Excludes fixed spectral alignment methods - Sibling: Excludes methods that use spectral features without explicit alignment

Suggested Search Directions: - Methods combining adaptive discrepancy learning with spectral basis alignment - Learnable spectral filters or wavelets for domain adaptation - Meta-learning approaches for spectral domain adaptation - Attention mechanisms over spectral components for cross-domain alignment

Sibling Subtopics

- **Spectral Regularization and Basis Alignment** (leaves: 1, papers: 3)
- Scope: Methods aligning graph domains by learning or matching spectral bases, eigenspaces, or frequency components of graph signals.
- Exclude: Methods using spectral features only as input without explicit spectral alignment belong elsewhere.

Contributions Analysis

Overall novelty summary. The paper proposes ADAlign, an adaptive framework for graph domain adaptation that automatically identifies and aligns distributional discrepancies without manual specification of alignment criteria. According to the taxonomy, this work resides in the 'Adaptive Spectral Discrepancy Alignment' leaf under 'Spectral and Graph-Theoretic Alignment'. Notably, this leaf contains only the current paper itself—no sibling papers are listed. This positioning suggests the work occupies a relatively sparse research direction within the broader spectral alignment branch, which itself contains only four papers total across two leaf nodes.

The taxonomy reveals that spectral alignment methods form a small but distinct cluster within the field. The sibling leaf 'Spectral Regularization and Basis Alignment' contains three papers focusing on fixed spectral bases or eigenspace matching. Neighboring branches include adversarial methods (five papers across two leaves), optimal transport approaches (four papers), and prototype-based alignment (four papers). The scope note for the current leaf explicitly distinguishes adaptive spectral discrepancy measures from fixed spectral alignment, suggesting the authors position their work as introducing flexibility to an otherwise rigid methodological category. This structural context indicates the paper bridges spectral theory with adaptive mechanisms, a combination not heavily explored in the examined literature.

Among fifteen candidates examined through semantic search and citation expansion, none were found to clearly refute any of the three main contributions. Contribution A (the ADAlign framework) examined ten candidates with zero refutable matches; Contribution B

(Neural Spectral Discrepancy) examined two candidates with zero refutations; Contribution C (minimax optimization with adaptive frequency sampler) examined three candidates with zero refutations. The limited search scope—fifteen papers rather than an exhaustive survey—means these statistics reflect the most semantically similar work rather than comprehensive prior art. The absence of refutable candidates suggests either genuine novelty within this search radius or that closely related work uses sufficiently different terminology or framing to avoid semantic overlap.

Given the sparse taxonomy leaf and limited search scope, the work appears to introduce a relatively unexplored combination of adaptive mechanisms and spectral alignment for graph domain adaptation. However, the analysis is constrained by examining only fifteen candidates from top-K semantic matches. The taxonomy structure shows spectral methods remain a minority approach compared to adversarial or transport-based techniques, which may explain both the sparse leaf population and the lack of directly competing prior work in the examined sample. A broader literature search beyond semantic similarity might reveal additional relevant work in adjacent methodological areas.

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

Contribution 1: ADAlign: Adaptive Distribution Alignment Framework for Graph Domain Adaptation

Description: The authors introduce ADAlign, a framework that automatically detects and aligns the most relevant distributional discrepancies in graph domain adaptation without requiring manual specification of alignment criteria. Unlike heuristic methods, it adapts to scenario-specific shifts by jointly capturing the interplay between attributes, structures, and their dependencies.

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. Gradual domain adaptation for graph learning

URL: View paper

Brief Assessment

Gradual domain adaptation for[4] focuses on constructing intermediate domain sequences via Fréchet mean over FGW metric and vertex-based progression for large distribution shifts. The original paper's ADAlign addresses automatic detection and alignment of distributional discrepancies using neural characteristic functions in the spectral domain, which is a fundamentally different technical approach.

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2. Collaborate to adapt: Source-free graph domain adaptation via bi-directional adaptation

URL: View paper

Brief Assessment

Collaborate to adapt[54] addresses source-free graph domain adaptation where the labeled source graph is inaccessible, while the original paper assumes access to labeled source graphs for alignment. These are fundamentally different problem settings with distinct technical requirements.

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3. Model-Free Graph Data Selection under Distribution Shift

URL: View paper

Brief Assessment

Model-Free Graph Data Selection[22] focuses on data selection for graph domain adaptation without relying on GNN models, while the original paper proposes an adaptive alignment framework using neural characteristic functions. These are fundamentally different approaches to the graph domain adaptation problem.

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

URL: View paper

Brief Assessment

Dynamic graph neural networks[55] addresses spatio-temporal distribution shifts in dynamic graphs through invariant pattern discovery, while the original paper focuses on cross-graph domain adaptation with static graphs using spectral alignment methods.

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5. Graph learning under distribution shifts: A comprehensive survey on domain adaptation, out-of-distribution, and continual learning

URL: View paper

Brief Assessment

Graph learning under distribution[14] is a survey paper that reviews existing graph domain adaptation methods but does not propose a novel adaptive framework itself. It categorizes existing approaches rather than introducing new technical contributions that would refute ADAlign's novelty.

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6. Graph domain adaptation: A generative view

URL: View paper

Brief Assessment

Graph domain adaptation[51] focuses on disentangling semantic, domain, and random latent variables using variational graph auto-encoders for graph classification tasks, whereas the original paper addresses node classification through adaptive spectral alignment of distributional discrepancies without requiring manual specification of alignment criteria.

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

URL: View paper

Brief Assessment

Out-of-distribution generalization on graphs[53] is a survey paper that reviews existing methods in the field. It does not present a novel adaptive framework for graph domain adaptation that automatically detects distributional discrepancies, which is the core novelty claim of the original paper.

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8. Causal-aware graph neural architecture search under distribution shifts

URL: View paper

Brief Assessment

Causal-aware graph neural architecture[52] focuses on neural architecture search under distribution shifts, not graph domain adaptation. It addresses discovering optimal GNN architectures through causal relationships, whereas the original paper addresses aligning distributional discrepancies between source and target graphs.

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9. Graph transfer learning via adversarial domain adaptation with graph convolution

URL: View paper

Brief Assessment

Graph transfer learning via[3] focuses on adversarial domain adaptation with graph convolution for cross-network node classification, using fixed Wasserstein distance and gradient penalty. It does not propose an adaptive framework that automatically detects scenario-specific distributional discrepancies or use neural characteristic functions in the spectral domain as ADAlign does.

10. Fine-Grained Graph Domain Adaptation via Instance Contrastive Learning

URL: View paper

Brief Assessment

Fine-Grained Graph Domain Adaptation[9] focuses on instance-level contrastive learning with dual-scale shift node embeddings, whereas the original paper proposes an adaptive framework using neural characteristic functions in the spectral domain to automatically detect distributional discrepancies without manual specification.

Contribution 2: Neural Spectral Discrepancy (NSD): Parametric Distance Using Neural Characteristic Function

Description: The authors propose Neural Spectral Discrepancy (NSD), a theoretically principled parametric distance metric that uses neural characteristic function in the spectral domain to encode feature-structure dependencies of all orders. A learnable frequency sampler adaptively emphasizes the most informative spectral components for each task via a minimax paradigm.

This contribution was assessed against **2 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Issues of integration of the inversion formula while calculating the distribution of output values of the GERT network

URL: View paper

Brief Assessment

The candidate paper focuses on GERT network analysis using characteristic functions for inversion formula integration in stochastic network modeling, not on parametric distance metrics for graph domain adaptation or distributional shifts.

2. Reciprocal GAN through characteristic functions (RCF-GAN)

URL: View paper

Brief Assessment

Reciprocal GAN through characteristic[59] focuses on generative modeling (GANs) for image and graph generation tasks, not on graph domain adaptation or distributional shift alignment. The application domains and technical objectives are fundamentally different.

Contribution 3: Minimax Optimization Framework with Adaptive Frequency Sampler

Description: The authors develop a minimax optimization framework that jointly optimizes source classification and spectral alignment. The framework includes an adaptive frequency sampler parameterized by a neural mixing distribution that learns to prioritize frequency regions with large domain discrepancies, enabling dynamic and efficient distribution matching.

This contribution was assessed against **3 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Min-Max Metric for Spectrally Compatible Waveform Design Via Log-Exponential Smoothing

URL: View paper

Brief Assessment

Min-Max Metric for Spectrally[57] addresses waveform design for active sensing systems using min-max metrics for spectral compatibility, not graph domain adaptation with neural characteristic functions and adaptive frequency sampling for distribution alignment.

2. Spectral Adversarial MixUp for Few-Shot Unsupervised Domain Adaptation

URL: View paper

Brief Assessment

Spectral Adversarial MixUp for[58] focuses on few-shot domain adaptation using spectral mixing for data augmentation, not on general distribution alignment frameworks with neural characteristic functions for graph domain adaptation.

3. Adversarial domain adaptation network with calibrated prototype and dynamic instance convolution for hyperspectral image classification

URL: View paper

Brief Assessment

Adversarial domain adaptation network[56] focuses on hyperspectral image classification using adversarial training with calibrated prototypes and dynamic instance convolution, not on minimax optimization with adaptive frequency sampling for spectral domain alignment in graph domain adaptation.

Appendix: Text Similarity Detection

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

References

- [0] Learning Adaptive Distribution Alignment with Neural Characteristic Function for Graph Domain Adaptation View paper
- [1] Bridging source and target domains via link prediction for unsupervised domain adaptation on graphs View paper
- [2] Learning causally invariant representations for out-of-distribution generalization on graphs View paper
- [3] Graph transfer learning via adversarial domain adaptation with graph convolution View paper
- [4] Gradual domain adaptation for graph learning View paper
- [5] PALA: Class-imbalanced graph domain adaptation via prototype-anchored learning and alignment View paper
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- [7] Beyond generalization: A survey of out-of-distribution adaptation on graphs View paper

- [8] Joint domain adaptive graph convolutional network View paper
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