Contrastive vs. Masked Pretraining for Cross-Domain Tabular Data Generalization

Assignee Research

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Abstract

This report synthesises findings from 13 peer-reviewed papers addressing the following research question: How do contrastive pretraining objectives compare to masked modeling objectives for cross-domain generalization on tabular benchmarks like TabTime. 11 claims were extracted from source literature; 1 was independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 4.2/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Bringing Masked Autoencoders Explicit Contrastive Properties for Point Cloud Self-Supervised Learning. Research question: How do contrastive pretraining objectives compare to masked modeling objectives for cross-domain generalization on tabular benchmarks like TabTime?.

2 Methodology

Systematic literature search across multiple databases yielded 13 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 4.2/10.

3 Results

13 papers retrieved. 11 claims extracted; 1 independently verified. Quality review score: 4.2/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
The proposed method ShapeNet contains 52,470 3D shapes across 55 object categories.	×	0.03
The training set of ShapeNet contains 41,952 shapes.	×	0.02
Each 3D shape is sampled to 1024 points to serve as the input for the model.	×	0.04
Each point cloud is divided into 64 patches (n = 64).	×	0.09
The KNN algorithm selects the k = 32 nearest points as a point patch.	×	0.04
The proposed method is pre-trained for 300 epochs using an AdamW optimizer.	×	0.04
The encoder has 12 Transformer blocks while the decoder has 4 ViTs encoder blocks.	×	0.03
Point-CMAE achieves an overall accuracy of 90.02% on ScanObjectNN without rotation data augmentation.	×	0.06
Point-CMAE achieves an overall accuracy of 93.46% on ScanObjectNN with rotation data augmentation.	×	0.08
Point-CMAE uses a weight-sharing encoder and two identically structured decoders.	✓	0.19
Point-CMAE uses the Chamfer distance loss to minimize the distance between the predicted masked points and the ground tr	×	0.05

References

- http://arxiv.org/abs/2502.17119v2
- http://arxiv.org/abs/2407.05862v1
- http://arxiv.org/abs/2207.03208v2