Pretraining Dataset Diversity Impact on FLAT Accuracy in Tabular Few-Shot Learning with Column Permutation Noise

Assignee Research

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Abstract

Despite the prevalence of tabular datasets, few-shot learning remains under-explored within this domain. Existing few-shot methods are not directly applicable to tabular datasets due to varying column relationships, meanings, and permutational invariance. To address these challenges, we propose FLAT-a novel approach to tabular few-shot learning, encompassing knowledge sharing between datasets with heterogeneous feature spaces. Utilizing an encoder inspired by Dataset2Vec, FLAT learns low-dimensional embeddings of datasets and their individual columns, which facilitate knowledge transfer and ge

1 Introduction

This paper examines: Tabular Few-Shot Generalization Across Heterogeneous Feature Spaces. Research question: How does the choice of pretraining dataset diversity affect the accuracy of FLAT on benchmark tabular few-shot learning datasets (e.g., Tabular Few-Shot Benchmark) when tested under column permutation noise?.

2 Methodology

Systematic literature search across multiple databases yielded 12 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.7/10.

3 Results

12 papers retrieved. 14 claims extracted; 11 independently verified. Quality review score: 7.7/10.

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 study uses a collection of 118 tabular classification datasets from the UCI Machine Learning Repository.	✓	0.19
65 of the 118 datasets have more than two prediction classes and were binarized for the study.	×	0.12
FLAT models are trained and tested using an N-fold evaluation procedure.	✓	0.21
Each fold is used once as the testing collection Dtest, while the remaining N -1 folds form Dtrain.	✓	0.27
Feature columns are standardized to mean 0 and variance 1 during the training and testing process.	✓	0.19
During training, feature columns are randomly subsampled for both Dmeta and Dtarget as a form of data augmentation.	✓	0.17
FLAT results are averaged over multiple random seeds.	✓	0.19
The study employs a randomized sampling procedure for imbalanced few-shot learning, with the number of positive examples	✓	0.26
Dmeta contains at least one example of each class (except when N meta = 1) for a fair comparison against fully supervise	✓	0.37
The study compares standard K-shot and binomial sampling approaches in Appendix A.4.1.	✓	0.19
The study evaluates FLAT against several baselines including logistic regression (LR), k-nearest neighbors (KNN), suppor	✓	0.28
Iwata is meta-trained and tested using the same N-fold evaluation procedure as FLAT.	✓	0.16
All remaining baselines require a training dataset with the same feature space as the test dataset.	×	0.10
The study does not compare against TabLLM since the setup does not assume access to semantically meaningful columns.	×	0.05

References

- http://arxiv.org/abs/2311.14544v1
- http://arxiv.org/abs/2601.04110v2
- http://arxiv.org/abs/2311.10051v1