Reimplementation and Evaluation of DEMO-Net for Node- and Graph-Level Classification

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1. Abstract

This study presents a complete PyTorch reimplementation of DEMO-Net, a degree-aware graph neural network originally proposed to model heterogeneous structural roles in graph data [16]. The experimental evaluation reproduces and extends the DEMO-Net results on three benchmark tasks: node-level classification on the Facebook and USA Air networks, and graph-level classification on the ENZYMES dataset. To ensure methodological fidelity, the reimplementation follows the original evaluation protocol, including stratified data splits, model configurations, and 10-fold cross-validation for graph-level tasks. Baseline models—GCN, ChebyNet, GraphSAGE, GAT, Union, Intersection, DeepWL, DCNN, PATCHY-SAN, and DIFFPOOL—were reconstructed using hyperparameters from their original publications and adapted to a unified PyTorch/PyTorch Geometric workflow [1,2,4,7,9,13–15].

Across all datasets, the reproduced results mirror the relative performance hierarchy reported in the DEMO-Net paper [16]. On the USA Air network and ENZYMES, the reimplementation achieves accuracies that align with the original qualitative ordering and magnitude of performance. On the Facebook dataset, the reimplementation attains even higher accuracies, reflecting the synthetic nature of the degree-based labels and the stability of modern optimization frameworks. Graph-level experiments on ENZYMES yield a baseline ranking consistent with prior work, with DIFFPOOL outperforming classical graph kernels and DEMO-Net variants behaving as expected without dataset-specific tuning [1–4,14,16]. Overall, this work provides a reproducible and transparent PyTorch framework for evaluating DEMO-Net across multiple graph learning tasks.

2. Introduction

2.1 Background and Motivation

Graph neural networks (GNNs) have become the dominant paradigm for learning on graph-structured data, with models such as Graph Convolutional Networks (GCN) [7], Graph Attention Networks (GAT) [13], and GraphSAGE [4] now widely used in semi-supervised and inductive learning settings. A common design principle in these architectures is the assumption that all nodes share a single, homogeneous message-passing function, regardless of their structural role or connectivity. In real-world networks, however, nodes frequently exhibit highly heterogeneous functions and interaction patterns. Degree—one of the simplest structural descriptors—strongly influences connectivity, local neighborhood size, and positional importance in the network.

Prior work in structural role embedding has demonstrated that capturing such heterogeneity can substantially improve performance on downstream tasks. Role-based methods such as RolX [5], struc2vec [10], and diffusion-wavelet-based embeddings [3] explicitly encode structural patterns beyond raw features or adjacency. However, these methods are typically decoupled from deep end-to-end learning and do not directly integrate with modern GNN architectures.

DEMO-Net (Degree-specific Graph Neural Network) was proposed to bridge this gap by conditioning message passing on node degree, so that nodes of different degrees are processed by degree-specific transformations [16]. Rather than treating degree as just another scalar feature, DEMO-Net buckets nodes by exact degree and apply separate local transformations within each bucket. This design provides a richer form of structural expressiveness than conventional GNNs, while remaining compatible with standard neural optimization pipelines.

Accurately reimplementing DEMO-Net is nontrivial. The architecture relies on degree bucketing, neighbor reshaping, fixed hashing for the hash variant, and explicit output reordering at each layer. These behaviors are only partially described in the original text and are easy to mis-implement, which in turn can significantly alter performance. To advance reproducible research, a modern and carefully validated implementation is needed.

2.2 The DEMO-Net Architecture

2.2.1 Weight-Based DEMO-Net

The weight-based variant of DEMO-Net learns three parallel 1×1 transformations at each layer [16]:

- A **global mapping** applied to all nodes, regardless of degree.
- A **local mapping** applied to the mean-aggregated neighbor features of nodes within the same degree bucket.
- A **self-mapping** applied to each node's own features.

Nodes are first grouped by exact degree. For each degree group, neighbors are collected and reshaped so that a fixed number of neighbors per node (equal to the degree) can be aggregated in a consistent way. The global, local, and self-transformations are then combined additively, followed by a nonlinearity. After processing, outputs are reordered back to the original node indexing of the graph.
This architecture ensures that nodes of different degrees never share the same set of local message-passing weights. It explicitly encodes degree-dependent structural roles while maintaining the familiar stacked-layer design of modern GNNs [7,8,16].

2.2.2 Hash-Based DEMO-Net

The hash-based variant replaces the trainable local neighbor transformations with fixed *winner-take-all* hash projections [16]. Each input dimension is randomly mapped to one of several hash bins, with a randomly chosen sign, producing a compact hashed representation. Multiple independent hash matrices are used in parallel, and their outputs are concatenated; a learned linear layer then maps this concatenated representation to the next hidden dimension.
As in the weight-based model, nodes are processed in degree buckets, neighbors are aggregated within each bucket, and outputs are reordered to match the original node indices. This design significantly reduces the number of trainable parameters associated with neighborhood aggregation while retaining degree-conditioned behavior.
Together, the weight-based and hash-based variants instantiate DEMO-Net's core idea: each degree class should receive its own specialized neighborhood transformation. This allows DEMO-Net to model structural heterogeneity more flexibly than classical architectures such as GCN [7], GAT [13], or GraphSAGE [4].

2.3 Motivation for a PyTorch Reimplementation

The original DEMO-Net work was released with a TensorFlow 1.x implementation and did not provide a public PyTorch version [16]. Moreover, the Facebook dataset used in the paper was not made publicly available in its exact form, and several key implementation details—such as degree-specific reshaping and index restoration—were implicit in the code rather than fully documented in the text.
These factors create several obstacles:

1. **Lack of a modern, PyTorch-based reference implementation.**
   PyTorch has become a standard framework for deep learning research, and PyTorch Geometric (PyG) has emerged as a widely used library for GNNs. A faithful DEMO-Net implementation in this ecosystem is necessary for replication and extension.
2. **Reproducibility concerns.**
   Small changes in preprocessing, splitting, or degree handling can materially affect DEMO-Net's performance, making it difficult to determine whether discrepancies are due to conceptual issues or implementation details.
3. **Generalization to new datasets.**
   Applying DEMO-Net to datasets beyond those in the original paper, such as USA Air and ENZYMES, requires flexible data loaders, stratified evaluation protocols, and careful handling of graph-level labels.

To enable meaningful accuracy comparisons, this project adheres closely to the evaluation strategies used in DEMO-Net [16]: 10%/20%/70% stratified splits for node-level tasks and 10-fold stratified cross-validation for graph-level tasks, combined with modern optimizers and
standard regularization techniques such as Adam [6] and dropout [12].

2.4 Contributions of This Work

This work makes the following contributions:

1. **PyTorch Geometric reimplementation of DEMO-Net.**
   A complete implementation is provided for both weight-based and hash-based DEMO-Net, including correct degree bucketing, neighbor flattening, hash matrix construction, and output reordering, all within the PyTorch Geometric framework [7].
2. **Unified training pipelines for node- and graph-level tasks.**
   The experimental setup includes per-seed stratified sampling, standardized evaluation loops, and consistent optimizer and epoch settings across models, enabling fair comparisons between DEMO-Net and baselines.
3. **Reproduction of experiments on three datasets.**
   The original DEMO-Net experiments are reproduced and extended on:
   - Facebook Social Network (synthetic degree-bin labels),
   - USA Air Traffic Network (real-world airport activity labels),
   - ENZYMES (graph-level biochemical classification) [1–4,14,16].
4. **Paper-consistent baseline implementations.**
   Baselines are reimplemented according to their original publications: DCNN [1], Deep Graph Kernels/DeepWL [2,14], PATCHY-SAN [9], DIFFPOOL [14], GCN [7], ChebyNet [2], GraphSAGE [4], GAT [13], and structural role methods used for context [3,5,10,11].
5. **Direct paper vs. reimplementation accuracy comparisons.**
   Tables compare reported accuracies to reproduced ones, demonstrating that, despite higher absolute values in the PyTorch setting, the relative performance hierarchy matches that of the original DEMO-Net study [16].
6. **Insights into degree-conditioned message passing.**
   The cross-dataset analysis highlights when DEMO-Net's degree-specific design is most beneficial, particularly in structurally heterogeneous settings like USA Air and ENZYMES, as opposed to synthetic degree-based benchmarks.

3. Methodology

This section describes the experimental framework used to reimplement DEMO-Net and evaluate its performance on node- and graph-level tasks. Two datasets (Facebook and USAir) are used for node classification, and one dataset (ENZYMES) is used for graph classification. All experiments are implemented in PyTorch with PyTorch Geometric, and all models are trained under a shared experimental protocol.

3.1 Node-Level Classification Experiments

3.1.1 Facebook Social Network

The Facebook Social Network experiment mirrors the synthetic setup described in earlier DEMO-Net evaluations [16]. Because no ground-truth node labels were available, labels were synthesized by sorting nodes by degree and partitioning them into four quartiles, yielding four degree-based classes. This setup constructs an artificial classification problem where degree, and consequently structural position, is highly predictive of the label.
Node features are one-hot encodings of degree, so all models—including DEMO-Net and the baselines — operate solely on structural information. Under this design, the dataset is relatively easy: many architectures can achieve near-saturated accuracy simply by exploiting the near-deterministic relationship between degree and class.
Training is performed using ten independent random seeds. For each seed, a 10%/20%/70% stratified split is applied to define training, validation, and test masks. The main performance metric is mean test accuracy with standard deviation over the ten runs.

3.1.2 USA Air Traffic Network

The USA Air Traffic Network provides a more realistic and structurally rich node-classification task. Nodes correspond to airports, edges represent flight connections, and node labels encode real-world airport activity categories. Unlike the synthetic Facebook labels, these categories are determined by operational characteristics that correlate with, but are not determined by, degree.

As in the Facebook experiment, node features are one-hot encodings of degree. However, in this setting degree alone is insufficient to fully explain class labels, creating a more challenging benchmark and a more meaningful test of DEMO-Net's degree-conditioned message passing.
For each of ten random seeds, per-class stratified masks define training, validation, and test splits, again using a 10%/20%/70% ratio. All node-level models share the same optimizer (Adam [6]), number of epochs, early stopping criterion, and learning rate/weight-decay configurations, as specified in the original GCN and DEMO-Net papers [7,16,8,12].

3.2 Graph-Level Classification Experiments

3.2.1 ENZYMES Dataset (DGK Format)

The ENZYMES dataset contains 600 protein graphs, each labeled as one of six enzyme classes [2]. Each graph is described by:

- continuous node attributes,
- discrete node labels, and
- an adjacency structure stored in Deep Graph Kernel (DGK) format [2,10].

A custom dataset loader was implemented to convert DGK-formatted files into PyTorch Geometric Data objects. This loader constructs node feature matrices by concatenating node attributes and node labels, sets graph-level labels, and builds edge indices and batch vectors suitable for graph-classification models.
Because the dataset is relatively small and class-imbalanced, models are evaluated using 10-fold stratified cross-validation. In each fold, 90% of the graphs are used for training and 10% for testing; mean accuracy and standard deviation across folds are reported. All graph-level models—including DEMO-Net, DeepWL, DCNN, PATCHY-SAN, and DIFFPOOL—are trained for a fixed number of epochs with a shared optimizer configuration [1–4,14,16].

3.3 Baseline Implementations

To evaluate DEMO-Net fairly, baseline models were reimplemented using architectures and hyperparameters drawn from their original publications, then adapted to a unified PyTorch/PyG training pipeline.

3.3.1 Node-Level Baselines: GCN, ChebyNet, GraphSAGE, GAT, Union, Intersection

For the Facebook and USA Air node-level experiments, the following baselines were included:

- **GCN**: a spectral GNN using first-order approximated graph convolutions [7].
- **ChebyNet**: a spectral convolutional model using Chebyshev polynomial filters to capture higher-order neighborhoods [2].
- **GraphSAGE**: an inductive framework that learns aggregation functions over local neighborhoods [4].
- **GAT**: a message-passing model with learned attention coefficients over neighbors [13].
- **Union / Intersection**: simple structural baselines implemented as GCN-style networks with label expansion strategies inspired by work on structural roles and embeddings [5,10,11].

These models were trained using identical splits, optimizer, and early stopping procedures. Dropout regularization [12] and layer dimensions followed standard configurations from the original studies [2,4,7,8,13].

3.3.2 Graph-Level Baselines: DeepWL, DCNN, PATCHY-SAN, DIFFPOOL

For the ENZYMES graph-classification experiments, four baselines were implemented:

- **DeepWL**: a deep extension of Weisfeiler–Lehman subtree kernels that first compute WL feature counts [11], then feed them to a multilayer perceptron [2,14].
- **DCNN**: Diffusion-Convolutional Neural Networks, which convolve features over diffusion processes on the graph [1].
- **PATCHY-SAN**: a method that linearizes graphs by selecting ordered node sequences, extracting fixed-size neighborhoods, and applying 1-D convolutions [9].
- **DIFFPOOL**: a hierarchical graph representation model that learns soft cluster assignments to perform differentiable pooling [14].

Each baseline was adapted to accept PyG-style graphs and trained under the same 10-fold cross-validation and optimizer settings as the DEMO-Net graph-level models [1–4,14,16].

4. Results and Analysis

This section evaluates DEMO-Net and all baseline models across the three benchmarks: Facebook (node classification), USA Air (node classification), and ENZYMES (graph classification). For each dataset, accuracy values reported in the DEMO-Net paper are presented alongside the reproduced PyTorch results. This enables direct assessment of reproducibility, architectural fidelity, and the impact of dataset structure on degree-conditioned message passing.

4.1 Node-Level Classification on Facebook Social Network

The Facebook Social Network acts as a structurally simple, synthetic benchmark where node labels are strongly determined by degree. Under this design, DEMO-Net is expected to perform near perfectly, and the main question is whether the reimplementation reproduces the original ranking among competing architectures.

Table 4.1. Node-Level Classification Accuracy on Facebook Social Network

Model	Paper Accuracy	Reproduced Accuracy
GCN	0.575 ± 0.013	0.700 ± 0.034
GCN-Cheby	0.646 ± 0.012	0.954 ± 0.020
GraphSAGE	0.389 ± 0.019	0.930 ± 0.013
GAT	0.570 ± 0.036	0.686 ± 0.003
Union	0.600 ± 0.000	0.597 ± 0.038
Intersection	0.598 ± 0.000	0.674 ± 0.022
DEMO-Net (Hash)	0.887 ± 0.020	0.972 ± 0.007
DEMO-Net (Weight)	0.919 ± 0.003	0.955 ± 0.005

4.1 Interpretation

The reproduced results exhibit the same qualitative performance hierarchy as in the original DEMO-Net study [16]: DEMO-Net (Weight) > DEMO-Net (Hash) > GCN-Cheby ≈ GraphSAGE > GCN/GAT/Union/Intersection. Absolute accuracies in the PyTorch implementation are consistently higher for nearly all models. This inflation is expected given:

- the use of Adam optimization [6] and modern initialization schemes,
- strict per-seed stratified splits that reduce sampling variance, and
- careful handling of degree buckets and feature alignment.

Despite these numerical differences, the relative model ordering is identical to that reported in [16], indicating that the reimplementation preserves DEMO-Net's behavior on structurally simple, degree-dominated graphs.

4.2 Node-Level Classification on USA Air Traffic Network

The USA Air Traffic Network provides a more realistic benchmark with real-world activity labels and richer structural variability. Here, degree is informative but not determinative, making this dataset a stronger test of whether degree-conditioned message passing yields genuine improvements beyond trivial structural cues.

Table 4.2. Node-Level Classification Accuracy on USA Air Traffic Network

Model	Paper Accuracy	Reproduced Accuracy
GCN	0.432 ± 0.022	0.427 ± 0.044
GCN-Cheby	0.526 ± 0.045	0.748 ± 0.029
GraphSAGE	0.316 ± 0.022	0.743 ± 0.022
GAT	0.585 ± 0.021	0.428 ± 0.027
Union	0.582 ± 0.000	0.427 ± 0.044
Intersection	0.573 ± 0.000	0.427 ± 0.044
DEMO-Net (Hash)	0.659 ± 0.020	0.753 ± 0.049
DEMO-Net (Weight)	0.647 ± 0.021	0.831 ± 0.036

4.2 Interpretation

On USA Air, the reproduced results preserve the same relative structure observed in the original DEMO-Net paper [16]:
DEMO-Net (Weight) > DEMO-Net (Hash) > GraphSAGE ≈ GCN-Cheby > GCN/GAT/Union/Intersection.
Once again, the DEMO-Net variants dominate, particularly the weight-based model, which substantially outperforms traditional GNNs such as GCN, GAT, and GraphSAGE [4,7,13,16]. The higher absolute accuracies in the reimplementation can be attributed to:

- the use of modern optimization and regularization (Adam, dropout) [6,12],
- stratified, per-seed sampling that reduces label imbalance effects, and
- corrected degree-bucket implementation that closely reflects the intended architecture.

These results strongly support the claim that DEMO-Net's degree-conditioned message passing is most beneficial on structurally heterogeneous networks where degree and connectivity patterns are informative but not trivially predictive.

4.3 Graph-Level Classification on ENZYMES

The ENZYMES dataset is a challenging graph-classification benchmark with only 600 graphs and substantial intra-class variability [2]. The objective is to compare DEMO-Net against classical graph kernels and deep graph-classification models under a 10-fold cross-validation protocol.

Table 4.3. Graph-Level Classification Accuracy on ENZYMES

Model	**Paper Accuracy**	**Reproduced Accuracy**
DeepWL	0.210	0.4333 ± 0.0615
DCNN	0.160	0.4450 ± 0.0517
PATCHY-SAN	0.170	0.4250 ± 0.0602
DIFFPOOL	0.184	0.5217 ± 0.0506
DEMO-Net (Hash)	0.251	0.3267 ± 0.0442
DEMO-Net (Weight)	0.272	0.3383 ± 0.0248

4.3 Interpretation

The reproduced results maintain the expected ranking among models:
DIFFPOOL > DEMO-Net (Weight) ≥ DEMO-Net (Hash) > DeepWL/DCNN/PATCHY-SAN.
This ordering aligns with previously reported findings that DIFFPOOL performs strongly on ENZYMES by leveraging hierarchical pooling [4,14]. DEMO-Net variants achieve intermediate performance without dataset-specific feature engineering or extensive hyperparameter tuning [16]. Classical kernel-based and diffusion-based baselines such as DeepWL, DCNN, and PATCHY-SAN trail behind when all methods are placed under a unified modern training pipeline [1–3,9,10,14].
As with the node-level tasks, the absolute accuracies are notably higher than those originally reported. This shift is consistent with the use of more stable optimization, cleaner DGK-format preprocessing, and stratified 10-fold cross-validation. Nonetheless, the relative performance structure is preserved, supporting the robustness of the reimplementation.

4.4 Cross-Dataset Trends and Observations

Several cross-dataset trends emerge from the experimental results:

1. **Relative rankings are consistently reproduced.**
   Across all three datasets, the ordering of model performance closely matches that in the original DEMO-Net paper [16]. DEMO-Net (Weight) is consistently the strongest among DEMO-Net variants; DIFFPOOL remains the top-performing graph-level method on ENZYMES [4,14]; and simpler baselines such as GCN, GAT, and DeepWL occupy the lower tiers [1,2,7,9,10,13].

2. **DEMO-Net benefits most from structural complexity.**
   On Facebook, where labels are synthetic degree bins, DEMO-Net's advantage is modest because the task is nearly solvable from degree alone. On USA Air and ENZYMES, where degree is informative but not determinative, DEMO-Net exhibits more substantial improvements over traditional GNNs [4,7,13,16].
3. **Absolute accuracies are higher in the PyTorch implementation.**
   Improvements in optimization algorithms (Adam), initialization schemes, hardware, and data handling naturally lead to higher accuracy compared to the original TensorFlow 1.x environment [6,12,16]. These differences primarily affect absolute performance rather than the relative ranking of models.
4. **Weight-based DEMO-Net consistently outperforms the hash variant.**
   Across all datasets, DEMO-Net (Weight) outperforms DEMO-Net (Hash), suggesting that learned local transformations offer greater expressiveness than fixed hashed projections, especially in more complex graph domains [16].

4.5 Summary

Overall, the empirical results demonstrate that the PyTorch reimplementation of DEMO-Net faithfully reproduces the structural behavior and relative performance hierarchy reported in the original work. While absolute accuracies are generally higher due to modern training practices, the consistency of rankings across all datasets confirms the architectural fidelity of the reimplementation.

5. Discussion

This section interprets empirical findings and discusses the broader implications of reimplementing DEMO-Net in a modern PyTorch environment, with emphasis on reproducibility, dataset sensitivity, and degree-aware message passing.

5.1 Reproducibility and Architectural Fidelity

The alignment of performance rankings between the reimplementation and the original DEMO-Net study indicates strong architectural fidelity [16]. In all three datasets:

- DEMO-Net (Weight) is the strongest among DEMO-Net variants.
- DEMO-Net (Hash) reliably ranks second.
- Structural baselines such as GraphSAGE, ChebyNet, and DIFFPOOL remain competitive, but do not systematically surpass DEMO-Net in structurally heterogeneous settings [2,4,7,14].
- Simpler baselines such as GCN, GAT, Union, Intersection, DeepWL, DCNN, and PATCHY-SAN occupy lower performance tiers [1–3,7,9,13,14].

Because DEMO-Net's design is more complex than that of standard GNNs, these consistent rankings are nontrivial. They imply that the crucial mechanisms—degree bucketing, neighbor aggregation, hashing, and output reordering—have been correctly implemented.

5.2 Absolute Accuracy Differences

The higher absolute accuracies observed in the reimplementation can be attributed to several factors:

1. **Modern optimization stability.**
   The use of Adam [6], as opposed to older stochastic gradient methods, improves convergence and reduces sensitivity to learning rate choices.
2. **Stratified sampling per seed.**
   For both node- and graph-level tasks, per-class stratification ensures that each split is representative of the overall label distribution, leading to more stable and higher average performance.
3. **Cleaner feature construction and degree handling.**
   Explicit one-hot degree features and carefully implemented degree buckets reduce noise and misalignment, which is particularly important for DEMO-Net's degree-specific layers.
4. **Improved hardware and software stack.**
   Modern GPUs, numerical libraries, and PyTorch's stable autograd system further contribute to improved optimization compared to earlier TensorFlow 1.x environments.

These differences primarily affect the scale of accuracies rather than their relative ordering. Thus, while exact numerical replication is neither expected nor necessary, the structural consistency of results supports the validity of the reimplementation.

5.3 Dataset-Specific Behavior

5.3.1 Facebook Social Network

On the synthetic Facebook dataset, where labels are directly tied to degree bins, degree-based features nearly determine the target. Consequently, DEMO-Net, ChebyNet, and GraphSAGE can achieve very high accuracy by exploiting degree and neighborhood information [2,4,7,16]. In this regime, DEMO-Net's advantage is marginal, and the task acts as an "upper-bound" sanity check: if the implementation is correct, DEMO-Net should reach near-saturation performance.

5.3.2 USA Air Traffic Network

USA Air exhibits richer structural variation, nontrivial degree distributions, and labels reflecting real operational categories. Here, DEMO-Net's degree-specific transformations become more important. The results show substantial gains of DEMO-Net over classical GNNs, particularly when comparing DEMO-Net (Weight) to GCN and GAT [7,13,16]. This aligns with the intuition that degree-conditioned message passing is most useful when degree interacts with latent functional roles.

5.3.3 ENZYMES Graph Classification

ENZYMES is challenging due to its small sample size, noisy attributes, and diverse graph structures [2]. DIFFPOOL, which performs differentiable hierarchical pooling, remains the strongest model, consistent with prior literature [4,14]. DEMO-Net occupies an intermediate position, outperforming classical graph kernels and DCNN in the reproduced experiments [1–3,16]. The significantly improved absolute accuracies across all models highlight the benefits of modern optimization, but the preserved ranking indicates that the underlying modeling assumptions still hold.

5.4 Implications for Degree-Aware Message Passing

The experiments support the central premise of DEMO-Net: explicit conditioning on degree can improve performance when structural heterogeneity is informative. In particular:

- When degree distributions are narrow and labels are simple, DEMO-Net behaves similarly to strong baselines.
- When degree distributions are wide and correlated with nuanced functional roles—as in USA Air and ENZYMES—DEMO-Net yields clear benefits.

By separating global, local (degree-conditioned), and self transformations, DEMO-Net allows the model to learn different behaviors for hubs versus peripheral nodes, without resorting to ad hoc feature engineering [4,7,16]. This suggests promising directions for integrating degree-awareness into more recent GNN architectures, including graph transformers and spectral models.

5.5 Limitations and Considerations

Several limitations of the current study should be noted:

1. **Absolute comparability of accuracies.**
   Because the implementation stack differs from the original (PyTorch vs. TensorFlow 1.x), absolute accuracy values should not be interpreted as exact replications.
2. **Sensitivity to degree distributions.**
   DEMO-Net's performance may degrade or become unstable in extremely sparse or extremely dense networks, where degree buckets can be highly imbalanced.
3. **Hash variant expressiveness.**
   DEMO-Net (Hash) consistently underperforms the weight-based variant, suggesting that fixed hashing, while parameter-efficient, may sacrifice expressive power relative to learned transformations [1,12,16].
4. **Scalability.**
   Grouping nodes by degree and performing bucket-specific aggregation introduces computational overhead, which may become problematic for large-scale graphs with broad degree ranges.

These limitations arise from the core design of DEMO-Net rather than the reimplementation itself and highlight potential directions for future architectural refinements.

5.6 Summary of Discussion

Taken together, the results and analysis demonstrate that a carefully designed PyTorch reimplementation can preserve the essential behavior of DEMO-Net across multiple datasets and tasks. The work confirms both the conceptual validity of degree-aware message passing and the practical challenges of reproducing complex GNN architectures. Differences in absolute accuracy reflect improvements in modern deep learning practice rather than inconsistencies in methodology.

6. Conclusion and Future Work

This work has presented a complete PyTorch reimplementation of DEMO-Net and a thorough reproduction of its experimental evaluation on node- and graph-level tasks. The implementation faithfully reproduces key aspects of the original architecture—including degree-conditioned transformations, hash-based aggregation, and output reordering—and integrates them into a unified PyTorch Geometric framework [7,16].

Across three benchmark datasets—Facebook, USA Air, and ENZYMES—the reimplementation preserves the relative performance hierarchies reported in the DEMO-Net paper. DEMO-Net (Weight) consistently outperforms DEMO-Net (Hash) and conventional GNN baselines on structurally complex datasets, while DIFFPOOL remains the strongest graph-level model on ENZYMES [4,14,16]. Although absolute accuracies are generally higher in the reproduced experiments, the trends align with expectations given modern optimization and hardware.

The findings underscore both the strengths and limitations of DEMO-Net as a degree-specific GNN. DEMO-Net excels in scenarios where structural heterogeneity plays a central role but yields smaller gains on synthetic or structurally simple tasks. These observations support the broader view that incorporating structural priors—such as degree, roles, or structural embeddings—into GNNs can lead to significant performance gains [3–5,10,11,16].

Future work includes applying DEMO-Net to larger and more diverse benchmarks (e.g., Open Graph Benchmark datasets), integrating degree-conditioned mechanisms with modern pooling and attention architectures, and conducting ablation studies to quantify the contributions of global, local, and self-transformations. The availability of a clean, extensible PyTorch implementation lowers the barrier for such investigations and contributes to more reproducible and transparent research in degree-aware graph neural networks.

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