Abstract—Graph Neural Network (GNNs) based methods have recently become a popular tool to deal with graph data because of their ability to incorporate structural information. The only hurdle in the performance of GNNs is the lack of labeled data. Data Augmentation techniques for images and text data can not be used for graph data because of the complex and non-Euclidean structure of graph data. This gap has forced researchers to shift their focus towards the development of data augmentation techniques for graph data. Most of the proposed Graph Data Augmentation (GDA) techniques are task-specific. In this paper, we survey the existing GDA techniques based on different graph tasks. This survey not only provides a reference to the research community of GDA but also provides the necessary information to the researchers of other domains.

Index Terms—Graph data augmentation

I. INTRODUCTION

Graph Neural Networks (GNNs) based methods have recently gained prominence because of their superior performance on graph data when compared to standard embedding-based approaches. The power of GNNs lies in their ability to model the structural information. GNNs are being widely used to perform tasks at three different levels including node, edge and graph. Node-level tasks such as node classification and missing data estimation aims to predict the label or missing data at a node in a graph. For example, predicting the class of a research paper in a citation network.

Edge-level tasks or edge prediction’s main objective is to predict whether there exists an edge between two nodes or not. For example, in recommendation system presence of an edge between two nodes will represent recommendation. Similarly, Graph-level tasks or graph classification goal is to predict the overall label of a graph. For example, given a chemical compound represented as a graph (nodes are atoms and edges represents the bond between them) classify it as toxic or non-toxic. Since GNNs make data-driven inferences and like all other data-driven models their performance can be boosted by having more data. One can always collect and label more data to increase the size of the training dataset. However, gathering and labeling data is expensive. Data augmentations are the techniques used to increase the amount of labeled data by creating slightly modified copies or new synthetic data from the existing labeled data. These techniques are inexpensive compared to gathering and labeling new data in most cases.

In the fields of Machine Learning (ML) and Natural Language Processing (NLP), data augmentation has been frequently used to expand the amount of training data. Unfortunately, these techniques cannot be directly used for graph data owing to their complex and non-Euclidean structure. In the recent years many researchers have focused on developing data augmentation techniques for GNNs resulting in an increasing number of graph data augmentation methods. In the current work, we survey the existing data augmentation works for GNNs and provide taxonomies for them according to different three different criteria. These criteria are summarized in Figure 2. Next three paragraphs briefly explain these taxonomies.

The graph data augmentation methods can be broadly divided into five classes based on augmentation techniques. These include node manipulation i.e. creation or removal of nodes from graphs, edge manipulation i.e. adding or dropping edges from a graph, The feature manipulation i.e. creating new features or modifying existing node/edge/graph features. Sub-graph manipulation is for graph-level tasks only and refers to cropping/modifying/swapping subgraphs within a graph. Figure 1 visually explains these techniques. Hybrid manipulation is just a mixture of two or more aforementioned augmentation techniques. Also, based on learning objective of GNNs GDA methods can be classified into two classes including supervised learning and unsupervised learning.

Similarly, based on end task GDA methods can be divided into three classes: link prediction, node classification and graph classification. For link prediction and node classification task, a single graph is used for both training and inference. Augmentation methods for these two tasks perform data augmentation by manipulating nodes/edges/features or combination of these operations. For example, Wang et al. proposed data augmentation method for link prediction that generates multiple augmented graphs by perturbing time and edges and then a multi-level module uses these graphs to make predictions. Rong et al. proposed data augmentation algorithm for node classification which randomly drops edges during training. For graph-level tasks we have multiple graphs and usually different set of graphs are used at training and inference stage.
Fig. 1: Graph Data Augmentation (GDA) Techniques for GNNs

Fig. 2: Taxonomy of Graph Data Augmentation (GDA) Methods for GNNs
So, data augmentation techniques for graph-level tasks generate new graphs from the limited number of available graph data by manipulating a subset of nodes/edges/features/sub-graph or any combination of these operations to improve generalization ability. For example, Wang et al. [51] first randomly selected an initial node and then generated new graphs by retaining the strongly connected sub-graph with the initial node.

Overall the main contributions of this work are as follows:

- For the new readers to quickly understand the similarities and differences between different works, we summarizes the existing work on the basis of three different criteria including the end task to be accomplished, augmentation technique and learning objective. Figure 3 summarizes the existing works in chronological order. Table I & II provides the list of papers divided by these taxonomies.
- Due to dataset variations and large number of evaluation metrics it becomes hard to compare the results of two different augmentation techniques. Our work facilitates to answer the question: which data augmentation technique works best for a specific task or on a specific dataset? The only way to do so is by building benchmarks similar to the other areas [6], [47].
- We summarizes the frequently used datasets and evaluation metrics for all papers. We hope this work would help community to build a good benchmark for this domain.
- To help researchers of this domain or individuals in general we also list the open-source implementations of the existing works in table VIII.

The rest of the paper is organized as follows. Section II provides some necessary background information about graphs and GNNs. Section III summarizes the node-level GDA methods. Section IV lists the graph-level GDA methods. Section VI briefly describes the edge-level GDA methods. Section VII provides the details of datasets and evaluation metrics being commonly used. For ease we divide them by task-level. Section VIII compares the performance of existing GDA methods. The last section provides future research directions and concludes this survey. In the appendix IX we provide the the links of open-source implementation of the existing works.

### II. BACKGROUND

In this section, we discuss notation for graph data and different types of graph data with examples.

#### A. Graphs

We denote a set of graphs as $G = \{G^p\}_{p=1}^n$, where $|G| = N$. Each graph $G^p$ is $(V^p, A^p)$ where $V^p$ is the set of $m$ nodes $\{v^p_1, v^p_2, ..., v^p_m\}$. $W^p$ is $m \times m$ matrix containing the edge weights $W_{i,j} \neq 0$ if there is an edge between $v^p_i$ and $v^p_j$, and 0 otherwise. $X^p$ is a $N \times d$ feature matrix, where $m^{th}$ row of $X^p_i$ denotes node feature of $v^p_m$.

#### B. Types of Graphs

**Directed Graphs Vs. Undirected Graphs.** A directed graph has direction information associated with each edge.

Consider, $e^p_{i,j} = (v^p_i, v^p_j)$ an edge between node $v^p_i$ and $v^p_j$ and $e^p_{i,i} = (v^p_i, v^p_i)$ an edge between node $v^p_i$ and itself. For directed graphs $e^p_{i,j} \neq e^p_{j,i}$. An example of a directed graph is Twitter, where each node is a user and an edge represents the follow-ship information. In undirected graphs, any two nodes share the same edge: $e^p_{i,j} = e^p_{j,i}$. For example, Facebook friendships is an undirected graph where nodes are users and the edge represents friendship.

**Dynamic Graphs Vs. Static Graphs.** A dynamic graph is the one whose nodes, edges, node features or edge features changes over time. Social networks are good examples of dynamic networks. A static graph has fixed set of node, edge, node features and edge features. A common example of static graph is molecular structure of drugs.

### C. Graph Neural Networks

Graph Neural Networks (GNNs) are a class of deep learning methods that are designed to perform node, edge and graph level inference on graph data. GNNs encode node features into low-dimensional to learn representation vectors $h_v$ for entire graph and for every node $v \in V$ respectively. Here we present the formal expression of Graph Convolution Network (GCN) [16]. The $k$-th layer of GCN is described as following:

$$
\begin{align*}
\text{msg}_v^{(k)}(j) &= \text{AGG}^{(k)}(\{h_v^{(k-1)} : j \in N(v)\}) \\
\text{h}_v^{(k)} &= \text{COMBINE}^{(k)}(h_v^{(k-1)}, \text{msg}_v^{(k)})
\end{align*}
$$

where $h_v^{(k)} \in \mathbb{R}^{n \times d_k}$ is the node representation at $k$-th layer. $N(v)$ represents the neighbors of node $v$. $\text{AGG}(.)$ is the aggregation function to collect node information via message passing. $\text{COMBINE}(.)$ combines the neighbors representation at $k$-th layer and node representation at $(k-1)$-th layer. Graph representation $h_G$ is obtained by using permutation-invariant $\text{READOUT}(.)$ function. This function pools node features from the the final iteration $K$ as follows:

$$
\text{h}_G = \text{READOUT}(\{h_v^{(K)} | v \in V\})
$$

### III. GRAPH DATA AUGMENTATION FOR NODE CLASSIFICATION

Given a network $G = (V, A, X)$ and a subset of labelled nodes $V_L \subseteq V$ with class labels from $Y = \{1, 2, ..., K\}$, where $K$ is the number of categories. The goal of the node classification algorithm is to learn a function $C : V \rightarrow Y$ that predicts the node label for each node $v \in V$. The function $C$ is usually learned by minimizing the cross-entropy loss between the predicted label and the original label of labeled nodes $V_L$. Node-level tasks are the most popular ones.

#### A. Data Augmentation Methods

Present data augmentation techniques for node classification can be broadly divided into four classes: 1) Edge Manipulation and 2) Node Manipulation 3) Feature Manipulation 4) Hybrid Manipulation.
For Node Classification

- DropEdge (2019) [32]
- NeuralSparse (2020) [68]
- TADropEdge (2021) [8]
- BGCN (2019) [64]
- GDC (2019) [17]
- DGI (2019) [44]
- Pro-GNN (2020) [13]
- AdaEdge (2020) [5]
- GAug (2021) [67]
- AutoGRL (2021) [39]
- NodeAug (2020) [53]
- GraphMix (2020) [45]
- Graph Mixup (2021) [52]
- NodeAug-I (2021) [57]
- FLAG (2020) [19]
- GRAND (2020) [7]
- GRACE (2020) [71]
- FairDrop (2021) [37]
- LA-GNN (2021) [24]
- Tang et al. (2021) [42]
- MV-GCN (2021) [62]

For Graph Classification

- GraphCrop (2020) [51]
- FLAG (2020) [19]
- M-Evolve (2020) [70]
- GrapCL (2020) [61]
- MoCL (2021) [40]
- JOAO (2021) [60]
- Graph Mixup (2021) [52]
- ifMixup (2021) [9]
- Graph Transplant (2021) [30]
- G-Mixup (2022) [11]
- GAMS (2022) [3]

For Link Prediction

- GraphMix (2020) [45]
- FLAG (2020) [19]
- MeTA (2021) [50]
- CFLP (2021) [65]

Fig. 3: Data Augmentation Techniques for GNNs.
TABLE I: Graph Data Augmentation Works Categorized on the basis of Learning Objective and End Task

| Learning objective      | End Task   | Paper |
|------------------------|------------|-------|
| Supervised Learning    | Link Prediction | [19], [50], [65] |
|                        | Node Classification | [5], [7], [8], [13], [17], [19], [32], [37], [39], [42], [45], [52], [52], [62], [66], [68] |
|                        | Graph Classification | [9], [19], [40], [51], [52], [70] |
| Unsupervised Learning  | Link Prediction | - |
|                        | Node Classification | [44], [53], [71] |
|                        | Graph Classification | [60], [61] |

TABLE II: Graph Data Augmentation Works Categorized on the basis of End Task and Augmentation Technique

| End Task       | Augmentation Technique   | Paper |
|----------------|-------------------------|-------|
| Link Prediction| Edge Manipulation       | [50], [65] |
|                | Node Manipulation       | [45]  |
|                | Feature Manipulation    | [19]  |
|                | Sub-Graph Manipulation  | -     |
|                | Hybrid Manipulation     | -     |
| Node Classification| Edge Manipulation | [5], [8], [13], [17], [32], [37], [62], [64], [67], [68] |
|                | Node Manipulation       | [45], [52] |
|                | Feature Manipulation    | [19], [24], [42], [44] |
|                | Sub-Graph Manipulation  | -     |
|                | Hybrid Manipulation     | [7], [39], [57], [57], [71] |
| Graph Classification| Edge Manipulation | [10]  |
|                | Node Manipulation       | [52]  |
|                | Feature Manipulation    | [19]  |
|                | Sub-Graph Manipulation  | [3], [9], [11], [30], [40], [51] |
|                | Hybrid Manipulation     | [60], [61] |

1) Edge Manipulation: Edge manipulation-based data augmentation techniques aim to manipulate the existing graph topology by adding some perturbation to the adjacency matrix of the graph. Rong et al. proposed DropEdge [32] that randomly drops a fixed percentage of edges at each training epoch. Dropping edges slightly modify the original graph and thus GNN sees a different graph at each epoch. DropEdge significantly improves the GNN model generalization capability and also helps in reducing the over-smoothing problem of GNN (especially in deeper GNN). One of the major concerns about DropEdge technique is that it may remove task-relevant edges and decrease the overall performance of GNN model. To cater to this issue, Zheng et al. proposed NeuralSparse [68] that uses MLP based model trained jointly with GNN on node classification loss and learns to drop only task-irrelevant edges. TADropEdge (Topology Adaptive Drop edge) [8] proposed by Gao et al. take into consideration the graph structural information when randomly dropping edges. In this way, the proposed technique makes sure that the augmented graph preserves the topological structure of the original graph. Similarly, Spinelli et al. [37] proposed FairDrop that biasedly drop edges to reduce the negative effects of homophily sensitive attributes.

Another work by Klicpera et al. proposed Graph Diffusion Convolution (GDC) [17], that utilizes Personalized PageRank (PPR) [29] or heat kernel [18] along with graph sparsification to create the diffused version of the graph. One of the benefits of GDC is that it can perform multi-hop message-passing without requiring any specific change in the model architecture. Jin et al. proposed Pro-GNN [13] that updates the graph structure iteratively with restrictions on the low-rank, sparsity, and feature smoothness properties.

Chen et al. proposed AdaEdge [5] that makes use of the homophily property of the graph and adds edges between nodes predicted to have the same label in the previous iteration and removes edges from the nodes having different labels. Similarly, Zhao et al. proposed GAug-M and GAug-O [67] which adds/drops edges based on the output of neural edge predictor. GAug-M modifies the original graph for future training and inference whereas GAug-O modifies the graph for training only.

Similarly, Multi-View Graph Convolution Network (MV-GCN) [62] learns two new views of the graph data that reveal the global and feature relationship between nodes. Then an attention-based model aggregates the information from the three views (i.e. local topology, global topology, feature similarity) to learn node representation.

2) Node Manipulation: Node manipulation based methods goal is to create or remove nodes from the graph data. Inspired from the Mixup [63] data augmentation technique for images that merges two images to create a new image. Verma et al. proposed GraphMix [45] as a replacement of Mixup for graph data. GraphMix is more like a regularization method that trains a fully-connected neural network along with GNN via parameter sharing. Following it Wang et al. [52] proposed Graph Mixup for node and graph classification. Graph Mixup is a two-branch convolution network. Given a pair of nodes, the two branches learn the node representation of each node and then the learned representations are aggregated at each hidden layer.

3) Feature Manipulation: Feature manipulation based techniques aim to manipulate the existing node features by either...
| Type          | Task-Level | Datasets | Source | #Nodes | #Edges | #Classes | Paper |
|--------------|------------|----------|--------|--------|--------|----------|-------|
| Citation     | Node/Edge  | Cora     |        | 2,708  | 5,429  | 7        | [5], [17], [18], [13], [17], [19], [24], [32], [39], [44], [45], [52], [53], [57], [62]. |
|              | Node/Edge  | Citeseer |        | 3,327  | 4,732  | 6        | [5], [17], [13], [17], [24], [32], [37], [42], [44]. |
|              | Node/Edge  | Pubmed   |        | 19,717 | 44,338 | 3        | [5], [17], [13], [17], [24], [32], [37], [42], [44]. |
|              | Node       | OGB-arxiv|        | 169,343| 1,166,243|          | [19]. |
| Coauthor     | Node       | CS       |        | 18,333 | 81,894 | 15       | [5], [17], [45], [53], [62]. |
|              | Node       | Physics  |        | 34,493 | 247,362| 5        | [5], [45], [53]. |
|              | Node       | ACM      |        | 3,025  | 13,128 | 5        | [5]. |
|              | Node       | DBLP     |        | 39,880 | 69,65  | 5        | [57]. |
| Traffic      | Node       | USA-Airports |       | 1,910  | 13,599 | 4        | [59], [66]. |
|              | Node       | WikiCS   |        | 10,711 | 216,123|          | [59]. |
|              | Node       | Amazon Computers |     | 13,581 | 245,778| 10       | [5], [17], [57], [62]. |
|              | Node       | Amazon Photos |      | 7,487  | 119,043| 8        | [5], [17], [39], [57], [62]. |
|              | Node       | OGB-Products |     | 2,490,299 | 61,859,140|      | [59]. |
|              | Node       | Amazon |        | 1,598,960 | 132,169,734| 107     | [59]. |
|              | Node/Edge  | Facebook |        | 4,039  | 88,234 | 2        | [5], [65]. |
|              | Node       | BlogCatalog |      | 7,003  | 119,743| 6        | [5], [66]. |
|              | Node       | Flickr    |        | 7,575  | 2,93,738| 9        | [52], [52], [66]. |
|              | Node/Edge  | Reddit   |        | 232,965| 11,606,919| 41       | [52], [54], [50], [66]. |
|              | Node       | Yelp      |        | 716,381| 63,977,410| 100      | [52], [54], [50], [66]. |
|              | Node       | Polblogs  |        | 1,222  | 16,714 | 2        | [5]. |
| Social       | Node       | OGB-DDI  |        | 4,267  | 1,334,889| -        | [11], [19], [65]. |
|              | Node       | OGB-Proteins |      | 132,334| 39,561,252|          | [19]. |
|              | Node       | PPI      |        | 10,076 | 157,213| 121      | [54], [66], [68]. |
| Collaboration| Node       | OGB-Collab |      | 235,868| 1,285,465| -        | [19]. |
|              | Node       | OGB-mag  |        | 1,939,743| 21,111,007|          | [19]. |
|              | Node       | UCLA2010 |        | 3,067  | 28,311 | 19       | [92]. |
|              | Edge       | Bitcoin Alpha |   | 3,785  | 24,180 | 2        | [5], [45]. |
|              | Edge       | Bitcoin OTC |      | 5,881  | 35,592 | 2        | [45]. |
|              | Node       | Squelch  |        | 5,201  | 217,073| 5        | [5], [64]. |
|              | Node       | Actor    |        | 7,060  | 33,544 | 5        | [5]. |
|              | Node       | Chameleon |       | 2,277  | 36,101 | 5        | [5]. |
|              | Edge       | MOOC     |        | 7,144  | 411,749|          | [58]. |
|              | Edge       | Wikipedia |        | 2,277  | 157,744| -        | [58]. |

adding noise to them or by mixing up features of two or more nodes.

Kong et al. proposed FLAG (Free Large-scale Adversarial Augmentation on Graphs) [19] which is not task-dependent and performs equally well on all the three tasks level (node, edge, and graph). The proposed algorithm iteratively augments node features by gradient-based perturbations. By making the model invariant to small perturbations the proposed model generalizes to out-of-distribution samples and hence gives better performance at test time. Local Augmentation for Graph Neural Networks (LA-GNN) [24] learns neighborhood information by conditioning on local structures and node features. The learned features are then concatenated with the original raw features before feeding it to the GNN. Tang et al. [42] creates multiple new graph topology (adjacency matrices) and node attributes (feature matrices) and then feeds them to specific GCN models to get node embeddings. Final node embeddings are an attentional combination of all the node embeddings.

4) Hybrid Manipulation: Hybrid manipulation based methods are the combination of two or more augmentation techniques i.e. they perform augmentation by manipulating two or more graph components. Wang et al. [53] said that structural modification influences neighboring nodes and sometimes can lead to undesired results. To cater to this issue they introduced the concept of “Parallel Universe”. Structural modification of augmenting each node is made in a parallel universe in a way that the changes made for one node do not influence other nodes. Feng et al. [7] proposed GRAND for graph data augmentation. GRAND uses consistency loss to minimize the distance between the representation learning of different augmented graphs. The augmented graphs are generated by randomly masking out some node features and dropping a percentage of nodes. Xue et al. [57] performs data augmentation by inserting new nodes into the graph. The labels and features of the inserted node are obtained by mixing the neighboring information with ratios $\lambda$ and $1 - \lambda$.

Sun et al. proposed AutoGRL (Automated graph represen-
TABLE IV: Summary of Datasets for Graph Classification

| Type       | Dataset Source | #Graphs | Avg. #Nodes | Avg. #Edges | #Classes | Paper |
|------------|----------------|---------|-------------|-------------|----------|-------|
| Social     |                |         |             |             |          |       |
|            | Reddit-Binary  | 2000    | 429.63      | 497.75      | 2        | [3], [11], [51], [60], [61] |
|            | Reddit-5K      | 4999    | 508.52      | 594.87      | 5        | [11], [40], [51], [60] |
|            | Reddit-12K     | 11929   | 391.41      | 456.89      | 11       | [11] |
| Chemical   |                |         |             |             |          |       |
|            | HIV            | 115     | 41.11      | 25.5        | 2        | [11], [19], [60] |
|            | lncRNA         | 1,513   | 35         | 35.5        | 2        | [11], [40], [60] |
|            | pcba           | 437,929 | 26.0       | 28.1        | 11       | [19] |
|            | tox21          | 1,513   | 18.6       | 19.3        | 2        | [60], [61] |
|            | bace           | 1,513   | 34.1       | 36.9        | 2        | [11], [40], [60] |
|            | ncba           | 437,929 | 26.0       | 28.1        | 11       | [19] |
|            | toxcast        | 1,513   | 18.6       | 19.3        | 2        | [60], [61] |
|            | clintox        | 1,513   | 26.0       | 28.1        | 11       | [19] |
|            | mutag          | 2,039   | 24.1       | 26.0        | 2        | [11], [40], [60] |
|            | mutag          | 2,039   | 24.1       | 26.0        | 2        | [11], [40], [60] |
|            | ENZYMES        | 2,039   | 24.1       | 26.0        | 2        | [11], [40], [60] |
| Co-featuring |                |         |             |             |          |       |
|            | IMDB-B         | 1000    | 243.4      | 2,266.1     | 2        | [19], [30], [60], [61] |
|            | IMDB-M         | 1500    | 243.4      | 2,266.1     | 2        | [19], [30], [60], [61] |
| Proteins   |                |         |             |             |          |       |
|            | OGB-ppa        | 158,100 | 243.4      | 2,266.1     | 2        | [19], [30], [60], [61] |
|            | OGB-code       | 452,741 | 243.4      | 2,266.1     | 2        | [19], [30], [60], [61] |
|            | Proteins       | 1113    | 26.0       | 28.1        | 11       | [19], [30], [60], [61] |
| Collaboration |                |         |             |             |          |       |
|            | Collab         | 5000    | 26.0       | 28.1        | 11       | [19], [30], [60], [61] |
| Anti-Cancer |                |         |             |             |          |       |
|            | NCI-H23        | 5000    | 26.0       | 28.1        | 11       | [19], [30], [60], [61] |
|            | MOE1-4         | 5000    | 26.0       | 28.1        | 11       | [19], [30], [60], [61] |
|            | P388           | 5000    | 26.0       | 28.1        | 11       | [19], [30], [60], [61] |
| Brain      |                |         |             |             |          |       |
|            | KKI            | 5000    | 26.0       | 28.1        | 11       | [19], [30], [60], [61] |
| Other      |                |         |             |             |          |       |
|            | NCI1           | 5000    | 26.0       | 28.1        | 11       | [19], [30], [60], [61] |
|            | NCI109         | 5000    | 26.0       | 28.1        | 11       | [19], [30], [60], [61] |
| D&D        |                |         |             |             |          |       |
|            | OTC            | 5000    | 26.0       | 28.1        | 11       | [19], [30], [61] |

TABLE V: Comparison of Data Augmentation Methods for Link Prediction with SOTAs. For GCN original architecture results in italics are % F1 Score.

| GNN Arch. | Algorithms | Measure | Cora | Citeseer | Pubmed | Reddit | MOOC | Bitcoin | Alpha | Bitcoin OTC |
|-----------|------------|---------|------|----------|--------|--------|------|---------|-------|-------------|
| GCN       | Original   | AUC     | 90.25| 71.47    | 96.33  | -      | -    | 64.00   | 65.72 |
|           | +CFLP [65] | AUC     | 92.55| 89.65    | 96.99  | -      | -    | -       | -     |
|           | +GraphMix  | % F1 Score | -   | -       | -       | -     | -    | 65.34  | 66.35 |
| TGN       | Original   | Accuracy | -   | -       | 92.56  | 81.38 | -    | -       | -     |
|           | +META [50] | Accuracy | -   | -       | 94.19  | 83.84 | -    | -       | -     |

IV. GRAPH DATA AUGMENTATION FOR GRAPH CLASSIFICATION

Given a set of graphs denoted by $G = \{G^p\}_{p=1}^n$, where $|G| = N$ and the associated label of $G^p$ is $y^p \in Y = \{1, 2, ..., K\}$, where $K$ is the number of categories. The goal of graph-level tasks is to predict the graph label of the unseen graph. A graph classifier $C$ parameterized by $\theta$ can be written as $C_\theta(G) = y^\theta$. Here $y^\theta$ is the predicted graph label. The classifier is trained by following the objection function described in equation $3$ Where $L(\cdot, \cdot)$ is the loss function to find a difference between true and predicted label and is usually cross-entropy loss.

$$min_\theta \Sigma_i L(C_\theta(G_i), y_i)$$  

A. Data Augmentation Methods

Existing data augmentation methods for graph classification can be further divided into five classes: 1) Edge Manipulation 2) Node Manipulation 3) Feature Manipulation 4) Sub-Graph Manipulation 5) Hybrid Manipulation.

1) Edge Manipulation: Zhou et al. [70] proposed M-Evolve algorithm that first finds motifs in the graph data and then...
TABLE VI: Node-Level Tasks Data Augmentation Methods Accuracy(%) Comparisons with SOTAs

| GNN Arch. | DA Technique | Algorithms | Cora | Citeseer | Pubmed |
|-----------|--------------|------------|------|----------|--------|
| GCN       | Original     | [16]       | 81.50| 70.30    | 79.00  |
|           | +DropEdge    | [32]       | 87.60| 79.20    | 91.30  |
|           | +NeuralSparse| [68]       | 83.50| 72.70    | 80.30  |
|           | +TADropEdge  | [8]        | 88.30| 81.40    | 91.50  |
|           | +AdaEdge     | [5]        | 82.30| 69.70    | 77.40  |
|           | +GAug-M      | [67]       | 83.60| 73.30    | 81.50  |
|           | +GAug-O      | [67]       | 83.60| 72.90    | 81.50  |
|           | +MV-GCN      | [62]       | 83.60| 72.90    | 81.50  |
|           | Node Augmentation |    | 83.94| 74.72    | 80.98  |
|           | +GraphMix    | [45]       | 90.00| 78.70    | 87.90  |
|           | +Graph Mixup | [52]       | 83.90| 73.08    | 81.10  |
|           | Feature Augmentation | | 84.10| 72.50    | 81.30  |
|           | +LA-GNN      | [24]       | 84.10| 72.50    | 81.30  |
|           | Tang et al.  | [42]       | -    | 74.60    | -      |
|           | Hybrid Augmentation | | 84.30| 74.90    | 81.30  |
|           | +NodeAug     | [53]       | 84.30| 74.90    | 81.30  |
| GAT       | Original     | [43]       | 83.00| 72.50    | 79.00  |
|           | +NeuralSparse| [68]       | 83.20| 71.50    | 79.00  |
|           | +AdaEdge     | [5]        | 82.30| 71.50    | 79.00  |
|           | +GAug-M      | [67]       | 82.20| 71.60    | -      |
|           | +GAug-O      | [67]       | 82.20| 71.60    | -      |
|           | Node Augmentation |    | 83.90| 72.30    | 81.60  |
|           | +GraphMix    | [45]       | 83.90| 73.08    | 81.10  |
|           | +Graph Mixup | [52]       | 83.90| 73.08    | 81.10  |
|           | Feature Augmentation | | 84.80| 75.10    | 81.60  |
|           | +LA-GNN      | [24]       | 84.80| 75.10    | 81.60  |
|           | Tang et al.  | [42]       | -    | 75.10    | -      |
|           | Hybrid Augmentation | | 84.30| 75.10    | 81.60  |
|           | +NodeAug     | [53]       | 84.30| 75.10    | 81.60  |
| GraphSAGE | Original     | [10]       | 81.30| 70.60    | 75.20  |
|           | +DropEdge    | [32]       | 85.00| 70.60    | 75.20  |
|           | +NeuralSparse| [68]       | 84.10| 73.60    | 91.70  |
|           | +AdaEdge     | [5]        | 82.00| 69.40    | 77.20  |
|           | +GAug-M      | [67]       | 83.20| 71.20    | -      |
|           | +GAug-O      | [67]       | 83.20| 71.20    | -      |
|           | Node Augmentation |    | 83.90| 70.20    | 78.10  |
|           | Hybrid Augmentation | | 82.30| 70.20    | 78.10  |

adds/removes edges within the motifs based on sampling weights.

2) Node Manipulation: Previously discussed Graph Mixup proposed by Wang et al. [52] a two-branch convolution network performs well for graph-level tasks as well.

3) Feature Manipulation: Aforementioned, FLAG (Free Large-scale Adversarial Augmentation on Graphs) [19] which augments node features by iteratively adding gradient-based perturbations can also be used for graph-level tasks.

4) Sub-graph Manipulation: Sub-graph manipulation based techniques are for graph-level tasks only and in these techniques we extract a sub-graph from a graph and perform cropping, swapping and modification operation on that sub-graph. For graph-level tasks, since we have independent graphs it is comparatively easy to transfer some of the CV and NLP-based augmentation techniques to graphs. Inspired from image cropping augmentation technique, Wang et al. proposed GraphCrop [51]. It first randomly selects an initial node and then forms a sub-graph by retaining the nodes that hold the strongest connectivity with the initial node. Sun et al. proposed MoCL [40] designed specifically for biomedical domain. MoCL selects functional group from a graph and replaces them with other semantically similar functional group.

Guo and Mao proposed ifMixup [9], that directly apply mixup on graph data by randomly assigning indices to nodes and then matching nodes on the basis of those indices. Park et al. proposed Graph Transplant [30] which first selects a sub-graph from both source graph based on salient node and then transplant the source sub-graph into the destination graph. Similarly, Han et al. proposed G-Mixup [11] for graph-level data augmentation. G-Mixup uses graphons to generate a class-level graph and then generate new data by mixing their graphons.

Graph augmentation with module swapping (GAMS) [4] partitions the graph into a fixed number of clusters, then computes the similarity score between the clusters of two graphs and swaps the clusters that are most similar to each other.

5) Hybrid Manipulation: GraphCL [61] augmentation algorithm carry out a combination of two or more augmentation techniques among the following techniques node augmentation (randomly remove nodes with their edges), edge augmentation (randomly add and drop edges), feature augmentation (mask out certain features randomly), and sub-graph augmentation (randomly sample a set of connected sub-graphs). Unfortunately, which combination of techniques to apply on a given data has to be hand picked by hit and errors because of the diverse nature of graph data. To solve this limitation You et al. proposed JOAO (Joint Augmentation Optimization) [60] that automates the selection GDA techniques for GraphCL.

V. GRAPH DATA AUGMENTATION FOR LINK PREDICTION

Given a dynamic graph $G = (V, E)$ in which each edge $e = (v_i, v_j) \in E$ represents an interaction between $v_i$ and $v_j$ that took place at a particular time $t$. We record multiple interactions between $v_i$ and $v_j$ as parallel edges, with
TABLE VII: Graph-Level Tasks Data Augmentation Methods Accuracy(%) Comparisons with SOTAs

| GNN Arch. | DA Technique | Algorithms       | Collab | IMDb-M | Reddit-5K | MUTAG | Proteins | NC1  |
|-----------|--------------|------------------|--------|--------|----------|-------|----------|------|
| GCN       | Original     |                  | 74.30  | 48.20  | 53.70    | 85.00 | 74.20    | 80.40|
| Node Augmentation | Graph Mixup [52] | 75.40  | 48.80  | 54.60  | -        | 74.1  | 77.7    |
| Subgraph Augmentation | GraphCrop [51] | 75.10  | 48.30  | 54.60  | -        | 74.0  | 77.5    |
| G-Mixup [11] | GAMS [3]     | 75.47  | 47.80  | 54.60  | -        | 74.0  | 77.5    |
|           | iMixup [9]   | -     | 52.30  | -      | 87.90    | 75.30 | 81.90   |
|           | GraphCL [61] | 74.23  | -      | 52.55  | -        | 74.17 | 74.63   |
|           | JOAO [60]    | 75.53  | -      | 52.83  | -        | 73.31 | 74.86   |
| Original  | Node Augmentation | Graph Mixup [52] | 75.50  | 48.50  | 56.10    | 81.50 | 74.50    | 79.30|
| G-Mixup [11] | GraphCrop [51] | 76.90  | 49.60  | 57.8    | -        | 74.1  | 80.9    |
| Subgraph Augmentation | Graph Mixup [11] | -     | 50.46  | 55.49  | -        | -     | -       |
| G-Mixup [11] | GraphCrop [51] | 76.90  | 49.60  | 57.8    | -        | 74.1  | 80.9    |
| G-Mixup [11] | Graph Transplant [30] | 81.50  | -      | -      | 82.80    | -     | 81.50   |
| iMixup [9] | -            | 76.5   | -      | 79.00  | 85.40    | 83.90 | 83.90   |

A. Data Augmentation Methods

Very few dedicated GDA methods have been proposed for the task of link prediction. Existing works can be classified into three categories: 1) Edge augmentation 2) Node augmentation 3) Feature manipulation.

1) Edge Manipulation: Wang et al. proposed MeTA [50] for temporal graph. A multi-level module in MeTA handles augmented graphs of various magnitudes on multiple levels. The augmented graphs are created by perturbing time and edges. Zhao et al. [65] method asks counterfactual questions of “would the link still exist if the graph structure became different from observation?” and learn to approximate unobserved outcome in the question.

2) Node Manipulation: Aforementioned GraphMix proposed by Verma et al. [45] works quite effectively for edge-level tasks as well. This method is inspired by Mixup [63] method from CV.

3) Feature Manipulation: Previously discussed FLAG [19] an adversarial attack based augmentation method works well for edge-level tasks.

VI. DATASETS AND EVALUATION METRIC

In this section, we will discuss the commonly used datasets as well as evaluation metrics for assessment of data augmentation algorithms.

A. Datasets

Table [IV] summarizes statistics of datasets being used for data augmentation works on graph data.

1) For Link Prediction: To the best of our knowledge, till now there are only four works in literature that explicitly proposed data augmentation algorithms for edge-level tasks. Among the four works only two share a common dataset OGB-DDI. CFLP [65] used Cora, Citeseer, Pubmed [36] citation network to evaluate their model performance. Where nodes are papers and edges represent citation links. Verma et al. [45] used Bitcoin Alpha and Bitcoin OTC [21] networks. The nodes in these networks represent bitcoin user and edge weight represent the level of trust between them. Wang et al. [50] uses three temporal datasets: MOOC [22], Reddit [2], and Wikipedia [22]. Reddit is a social network where a node is a user and an edge represents their interaction on the reddit thread. MOOC is a temporal and directed user action network. In MOOC networks, nodes are users and course activities whereas edge represents action by users on course activities. Similarly, Wikipedia is a temporal network of Wikipedia page edits. An edge represents that the user edited the page at a specific time.

2) For Node Classification: Cora, Citeseer, and Pubmed [36] are the three commonly used datasets to evaluate data augmentation algorithms for node-level tasks. All three datasets are undirected citation networks where nodes are documents and edges are citation links. The features are sparse bag-of-words vectors. For training, only 20 nodes per class were used i.e. 140 nodes for Cora, 120 nodes for Citeseer, and 60 nodes for Pubmed.

3) For Graph Classification: For Graph-level task Collab [59], IMDb-M, Reddit-5K [2], Proteins [15], MUTAG [14], and NC11 [46] undirected networks are being widely used for evaluating model performance. Collab is a scientific collaboration network where nodes in each graph are researchers and the edge indicates the collaboration between two researchers. IMDb-M is a co-featuring network of actors/actresses where nodes in each graph are actors/actresses and the edge indicates that the actor/actress worked in the same movie. Reddit-5K is a social network where each graph is a discussion thread. Nodes in each graph are users and an edge is showing whether a user responded to another user or not. Proteins is datasets of proteins and the goal is to classify proteins as enzymes and non-enzymes. Node represents the amino acids and edge represents that the nodes/peptide acids are less than 6 Angstroms apart. MUTAG is a collection of nitroaromatic compounds where each graph represents a chemical compound. The nodes in the graph are atoms and edge represents bond between atoms. Similarly, NC11 is also a collection of chemical compounds where a graph is a chemical compound. Nodes represents atoms and edges denote the bond between...
the atoms. NCI1 dataset is relative to anti-cancer screens where the chemicals are assessed as positive or negative to cell lung cancer.

B. Evaluation Metrics

In this section, we summarize the commonly used evaluation measures in the data augmentation for graph data literature. For convenience, we divide them on the basis of end task.

1) For Link Prediction: In this section, we briefly describe commonly used evaluation metrics for edge-level tasks. We could not find a common evaluation metric among the edge-level tasks prior works and hence will report the evaluation metric used in each paper separately. Verma et al. [45] uses F1-score as evaluation metric. Zhao et al. used AUC as the link prediction evaluation metric in their work [65]. Wang et al. in their work [50], evaluated their model performance by test accuracy.

2) For Node Classification: Most of the existing data augmentation algorithms [5], [17], [19], [32], [42], [53] for node-level tasks use classification accuracy as an evaluation metric. Apart from accuracy, F1-Score [54] and Area-Under-the-ROC-Curve AUC [55] is also used by some works such as [52], [68]. Value of accuracy for an algorithm must lie between 0 to 100 and values close to 100 represent superior performance whereas value of F1-score and AUC must lie in the range 0 to 1 and a value of 1 represents 100% perfect prediction.

3) For Graph Classification: Existing data augmentation algorithms [5], [9], [40], [51], [60], [61] for graph-level tasks mostly use classification accuracy as performance evaluation metric except for few. MoCL [40] that is using Area-Under-the-ROC-Curve AUC [55] as evaluation metric. Similarly, FLAG [19] uses Area-Under-the-ROC-Curve AUC [55], F1-score [54] and Average precision

VII. PERFORMANCE COMPARISON

In this section we compare the performance of existing graph data augmentation methods on the commonly used datasets for each task-level separately. For fair comparison the results are directly taken from the respective original paper.

A. For Link Prediction

In this section, we compare the performance of the proposed DA techniques against state-of-the-arts (SOTAs) GNN architectures GCN [16], and TGN [53]. Table VI compare the performance of edge-level DA techniques with SOTAs. CFLP [65] DA technique improves AUC of GCN [16] by 2.3%, 18.18%, and 0.66% on Cora, Citeseer, and Pubmed datasets respectively. GraphMix [45] DA technique shows slight improvement of 0.98% (averaged over both datasets) in % F1 score for Bitcoin Alpha and Bitcoin OTC datasets in comparison to original GCN [16]. MeTA [50] showed an improvement of 1.63% in test accuracy as compared to TGN [53] on Reddit dataset.

B. For Node Classification

This section compares the performance of the existing data augmentation methods for node-level tasks against state-of-the-arts (SOTAs) GNN architectures GCN [16], GAT [43], and GraphSAGE [10]. Table VII provides the accuracy (%) comparison of existing data augmentation methods with SOTAs.

Edge Manipulation based DA Methods: For the GCN [16] architecture, all the proposed DA methods showed an improvement in accuracy on all the three datasets except for the Pubmed dataset in the case of AdaEdge [5] for which we observed a 1.6% decrease instead. TADropEdge [8] proposed by Gao et al. gave the best performance on all three datasets for GCN architecture. For Cora, Citeseer, and Pubmed an increase of 6.8%, 11.1%, and 12.5% respectively was observed. For the GAT [43] GNN architecture, NeuralSparse [68] gave the best performance. Similarly, for GraphSAGE [10] GNN architecture DropEdge [32] gave the best performance. For GCN, we observed an overall 10.13% increase in the accuracy(averaged over all the datasets). For GAT, an overall 5.27% increase in accuracy was recorded (averaged over all the datasets). Similarly, for GraphSAGE there was an overall 10.9% increase in accuracy (again averaged over all the datasets).

Node Manipulation based DA Methods: For the GCN [16] architecture, Graph Mixup [52] augmentation technique showed an average 8.6% increase in accuracy across the three datasets, whereas as GraphMix [45] performed well on Citeseer dataset and showed a 0.58% increase in accuracy. For GraphSAGE [10], DropEdge [32] gave best performance on all the three datasets and showed an average increase of 10.9% in test accuracy.

Feature Manipulation based DA Methods: For GCN [43], Tang et al. data augmentation method showed an increase of 4.3% on citeseer dataset and an increase of 2.6% was observed on cora dataset for LA-GNN [24] data augmentation method. For GAT [43], LA-GNN [24] was able to increase testing accuracy for Cora dataset by 0.9%.

Hybrid Manipulation based DA Methods: For the GCN [16] architecture, NodeAug [57] proposed methods showed slight improvement in accuracy for Cora and Citeseer dataset. However, for Pubmed, the accuracy decreased by 0.2%. For GAT [43], NodeAug accuracy improved by 0.4% for only Cora dataset. For both Citeseer and Pubmed the accuracy declined. Whereas in the case of GraphSAGE [10] GNN architecture, NodeAug couldn’t perform better than the original GraphSAGE.

C. For Graph Classification

In this section, we compare the performance of the proposed DA techniques against state-of-the-art (SOTAs) GNN architectures GCN [16], and GIN [58]. Table VII provides the accuracy (%) comparison of proposed DA techniques with SOTAs. For graph-level tasks, a single augmentation technique failed to perform well on all the datasets. In the case of GCN [16] GNN architecture, GAMS [3] performed best on Collab dataset, G-Mixup [11] gave the best results for IMDB-M.
dataset whereas all the discussed data augmentation techniques were not able to show any improvement in case of Reddit-5K dataset. For GIN [56] architecture, Graph Transplant [30] showed a 6% increase in performance for Collab dataset, G-Mixup [11] performed well on IMDB-M dataset with an improvement of 1.96% in test accuracy, and Graph Mixup [52] showed slight performance improvement for Reddit-5k dataset.

VIII. CONCLUSIONS AND FUTURE DIRECTIONS

In this work, we compare all the existing graph data augmentation techniques to the best of our knowledge. We divide the existing works on the basis of task-levels and briefly describes the existing methods for each task-level. Then, we share most commonly used datasets and evaluation metrics for each task-level. Later, we also provide performance comparison of existing GDA techniques on commonly used datasets.

A. Future Directions

We now summarize a few limitations we have found in this field of research and offer some suggestions for the future works:

- Most of the existing data augmentation methods focus on node-level (especially node classification) and graph-level (especially graph classification) tasks and very few attention is paid to edge-level tasks. There is also opportunity in real-life tasks such as graph-based recommendation, search etc.

- To the best of our knowledge, FLAG proposed by Kong et al. [19] is the only GDA algorithm that is not specified to a particular task-level i.e node-level, edge-level, and graph-level and performs equally well on all the three task-levels. There is a potential for more generic algorithms like FLAG.

- Most of the existing data augmentation works cannot be used for molecular data because randomly adding/removing edges or cropping a subset of graph may lead to invalid molecular structure. To mitigate this issue their is a need to come up with more generalized graph data augmentation methods.

- Most existing works do not study the efficiency and scalability of graph data augmentation methods on larger networks. As we know that real-world network can be massive so this aspect cannot be ignored.

IX. APPENDIX

In this work, we not only survey the existing GDA techniques but also provide the details of commonly used datasets and evaluation metrics. Moreover, in table VIII we provide a link to open-source implementation in hope of facilitating the research community.
TABLE VIII: Summary of open-source implementation of algorithms

| Task Level | Paper | Algorithm | Link |
|------------|-------|-----------|------|
| DropEdge   | `https://github.com/DropEdge/DropEdge` |
| GAug-M, GAug-O | `https://github.com/zhao-tong/GAug` |
| NeuralSparse | `https://github.com/MingCheng/PyTorchNet` |
| Pro-GNN | `https://github.com/ChandlerBang/Pro-GNN` |
| FLAG | `https://github.com/devnkong/FLAG` |
| LA-GNN | `https://github.com/SoungHee0825/LAGNN` |
| GDC | `https://github.com/gastergerojo/edc` |
| GraphMix | `https://github.com/vikasverma107/GraphMix` |
| Graph Mixup | `https://github.com/vanovacac/MixupForGraph` |
| AutoCRL | `https://github.com/univsun/AutoCRL` |
| GRAND | `https://github.com/Grand20/grand` |
| DGI | `https://github.com/PetarV-DGI` |
| GRACE | `https://github.com/CRIPAC-DIG/GRACE` |
| MoCL | `https://github.com/ilidilanlab/MoCL_DK` |
| GAMS | `https://github.com/ripper346-pld/graph-cluster` |
| GraphCL | `https://github.com/Shen-Lab/GraphCL` |
| JOAO | `https://github.com/Shen-Lab/GraphCL_Automated` |
| CFLP | `https://github.com/DM2-ND/CFLP` |

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