Early-Bird GCNs: Graph-Network Co-Optimization Towards More Efficient GCN Training and Inference via Drawing Early-Bird Lottery Tickets

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Abstract

Graph Convolutional Networks (GCNs) have emerged as the state-of-the-art deep learning model for representation learning on graphs. However, it remains notoriously challenging to train and inference GCNs over large graph datasets, limiting their application to large real-world graphs and hindering the exploration of deeper and more sophisticated GCN graphs. This is because as the graph size grows, the sheer number of node features and the large adjacency matrix can easily explode the required memory and data movements. To tackle the aforementioned challenges, we explore the possibility of drawing lottery tickets when sparsifying GCN graphs, i.e., subgraphs that largely shrink the adjacency matrix yet are capable of achieving accuracy comparable to or even better than their full graphs. Specifically, we for the first time discover the existence of graph early-bird (GEB) tickets that emerge at the very early stage when sparsifying GCN graphs, and propose a simple yet effective detector to automatically identify the emergence of such GEB tickets. Furthermore, we advocate graph-model co-optimization and develop a generic efficient GCN early-bird training framework dubbed GEBT that can significantly boost the efficiency of GCN training by (1) drawing joint early-bird tickets between the GCN graphs and models and (2) enabling simultaneously sparsification of both the GCN graphs and models. Experiments on various GCN models and datasets consistently validate our GEB finding and the effectiveness of our GEBT, e.g., our GEBT achieves up to 80.2% $\sim$ 85.6% and 84.6% $\sim$ 87.5% savings of GCN training and inference costs while offering a comparable or even better accuracy as compared to state-of-the-art methods. Our source code and supplementary material are available at https://github.com/RICE-EIC/Early-Bird-GCN.

1 Introduction

Graph convolutional networks (GCNs) (Kipf and Welling 2016) have emerged as state-of-the-art (SOTA) algorithms for graph-based learning tasks, such as graph classification (Xu et al. 2018) and node classification (Kipf and Welling 2016). It is well recognized that the superior performance largely benefits from GCNs' ability for handling irregularity and unrestricted neighborhood connections. Specifically, for each node in a graph, GCNs first aggregate neighbor nodes' features, and then transform the aggregated feature through (hierarchical) feed-forward propagation to update the feature of the given node.

Despite their promise, GCN training and inference can be notoriously challenging, hindering their great potential from being unfolded in large real-world graphs. This is because as the graph dataset grows, the large number of node features and the abundant adjacency matrix can easily explode the required memory and data movements (Geng et al. 2021; Zhang et al. 2021). For example, a mere 2-layer GCN model with 32 hidden units requires 19 GFLOPs (FLOPs: floating point operations) to process the Reddit graph (Tailor, Fernandez-Marques, and Lane 2020), twice as much as that of a powerful deep neural network (DNN) ResNet50, which has a total of 8 GFLOPs when processing ImageNet (Canziani, Paszke, and Culurciello 2016). The giant computational cost of GCNs comes from three aspects. First, graphs (or graph data), especially real-world ones, are often extraordinarily large and irregular as exacerbated by their intertwined complex neighbor connections, e.g., a total of 232,965 nodes in the Reddit graph with each node having about 50 neighbors (Kersting et al. 2016). Second, the dimension of GCNs' node feature vectors can be very high, e.g., each node in the Citeseer graph has 3703 features. Third, the extremely high sparsity and unbalanced distribution of non-zero data in GCNs' adjacency matrices imposes a paramount challenge for effectively accelerating GCNs (Geng et al. 2020; Yan et al. 2020), e.g., as high as 99.9% vs. 10% to 50% generally observed in DNNs.

To tackle the aforementioned challenges and unleash the full potential of GCNs, various techniques have been developed. For instance, Tailor et al. (Tailor, Fernandez-Marques, and Lane 2020) leverages quantization-aware training to demonstrate 8-bit GCNs; SGCN (Li et al. 2020b) is the first to consider GCN sparsification by formulating and solving it as an optimization problem.

The impressive performance achieved by existing GCN compression works indicates that there are redundancies within GCNs to be leveraged for aggressively trimming down their complexity while maintaining their performance. In this work, we attempt to take a new perspective by drawing inspiration from the tremendous success of DNN compression, particularly the lottery ticket (LT) finding (Frankle and Carbin 2019; Liu et al. 2018; You et al. 2020). While conceptually simple, the unique structures of GCNs make it not straightforward to leverage the LT finding to compress GCNs. This is because (1) the graph instead of the MLPs in GCNs dominates the complexity, for which the existence of LT remains unknown; and (2) it is unclear how to jointly optimize the two phases of GCN operations (i.e., feature *aggregation* and *combination*) while doing so promises the maximum complexity reduction.

This paper aims to close the above gap to minimize the complexity of GCNs without hurting their competitive performance, and to make the following contributions:

- We discover the existence of graph early-bird (GEB) tickets that emerge at the very early stage when sparsifying GCN graphs, and propose a simple yet effective detector to automatically identify the emergence of GEB tickets. To our best knowledge, we are the first to show that the early-bird tickets finding holds for GCN graphs.
- we advocate graph-network co-optimization and develop a generic efficient GCN training framework dubbed GEBT that significantly boosts GCN training efficiency by (1) drawing joint early-bird (EB) tickets between the GCN graphs and models and (2) simultaneously sparsifying both the GCN graphs and models, additionally boosting the GCN inference efficiency.
- Experiments on various GCN models and datasets consistently validate our GEB finding and the effectiveness of the proposed GEBT. For example, our GEBT achieves up to 80.2% $\sim$ 85.6% and 84.6% $\sim$ 87.5% GCN training and inference costs savings while leading to a comparable or even better accuracy as compared to state-of-the-art (SOTA) methods.

2 Related Works

Graph Convolutional Networks (GCNs). GCNs have amazed us for processing non-Euclidean and irregular data structures (Zhang et al. 2018). Recently developed GCNs can be categorized into two groups: spectral and spatial methods. Specifically, spectral methods (Kipf and Welling 2017; Peng et al. 2020) model the representation in the graph Fourier transform domain based on eigen-decomposition, which are time-consuming and usually handle the whole graph simultaneously making it difficult to parallel or scale to large graphs (Gao et al. 2019; Wu et al. 2020). On the other hand, spatial approaches (Hamilton, Ying, and Leskovec 2017; Simonovsky and Komodakis 2017), which directly perform the convolution in the graph domain by aggregating the neighbor nodes' information, have rapidly developed recently. To further improve the performance of spatial GCNs, Veličković et al. (Veličković et al. 2018) introduce the attention mechanism to select information which is relatively critical from all inputs; Zeng et al. (Zeng et al. 2019) propose mini-batch training to improve GCNs' scalability of handling large graphs; and (Xu et al. 2019) theoretically formalizes an upper bound for the expressiveness of GCNs. Our GEB finding and GEBT enhance the understanding of GCNs and promote efficient GCN training, and can be generally applicable to SOTA GCN models.

GCN Compression. The prohibitive complexity and powerful performance of GCNs have motivated growing interest in GCN compression. For instance, Tailor et al. (Tailor, Fernandez-Marques, and Lane 2020) for the first time show the feasibility of adopting 8-bit integer arithmetic representation for GCN inference without sacrificing the classification accuracy; two concurrent pruning works (Li et al. 2020b; Zheng et al. 2020) aim to sparsify the graph adjacency matrices; and Ying et al. (Ying et al. 2018) propose a DiffPool layer to reduce the size of GCN graphs by clustering similar nodes during training and inference. Our GEBT explores from a new perspective and is complementary with exiting GCN compression works, i.e., can be applied on top of them to further reduce GCNs' training/inference costs.

Early-Bird Tickets Hypothesis. Frankle et al. (Frankle and Carbin 2019) show that winning tickets (i.e., small subnetworks) exist in randomly initialized dense networks, which can be retrained to restore a comparable or even better performance than their dense network counterparts. This finding has attracted lots of research attentions as it implies the potential of training a much smaller network to reach the accuracy of a dense, much larger network without going through the time and cost consuming pipeline of fully training the dense network, pruning and then retraining it to restore the accuracy. Later, You et al. (You et al. 2020) demonstrate the existence of EB tickets, i.e., the winning tickets can be consistently drawn at the very early training stages across different models and datasets, and leverages this to largely reduce the training costs of DNNs. More recently, the EB finding has been extended to natural language processing (NLP) models (e.g., BERT) (Chen et al. 2021b) and generative adversarial networks (GANs) (Mukund Kalibhat, Balaji, and Feizi 2020). Our GEB finding and GEBT draw inspirations from the prior arts, and for the first time demonstrate that the EB phenomenon holds for GCNs which have unique and different algorithm structures as compared to DNNs, NLP, and GANs. Furthermore, compared with the iterative pruning method, e.g., UGS (Chen et al. 2021a), we **for the first time** show that *early-bird (EB)* tickets exist in both GCN graphs and networks, and further develop efficient and effective detectors to automatically identify them, boosting both training and inference efficiency, while UGS draws *lottery tickets* after *fully and iteratively (up to 20×)* training the dense models for only saving inference costs.

3 Our Findings and Proposed Techniques

3.1 Preliminaries of GCNs and GCN Sparsification

GCN Notation and Formulation. Let $G = (V, E)$ represents a GCN graph, where $v_i \in V$ and $(v_i, v_j) \in E$ denote the nodes and edges, respectively; and $N = |V|$ and $M = |E|$ denote the total number of nodes and edges, respectively. The node degrees are denoted as $d = \{d_1, d_2, \cdots, d_N\}$ where d_i indicates the number of neighbors connected to the node v_i. We define D as the degree matrix whose diagonal elements are formed using d. Given the adjacency matrix A and the feature matrix $X = \{x_1, x_2, \cdots, x_N\}$ of the graph G, a two-layer GCN model (Kipf and Welling 2017) can then be formulated as:

$$Z = f(A, X) = \text{softmax}\left(\hat{A}\,\text{ReLU}\left(\hat{A}XW_0\right)W_1\right), \quad (1)$$

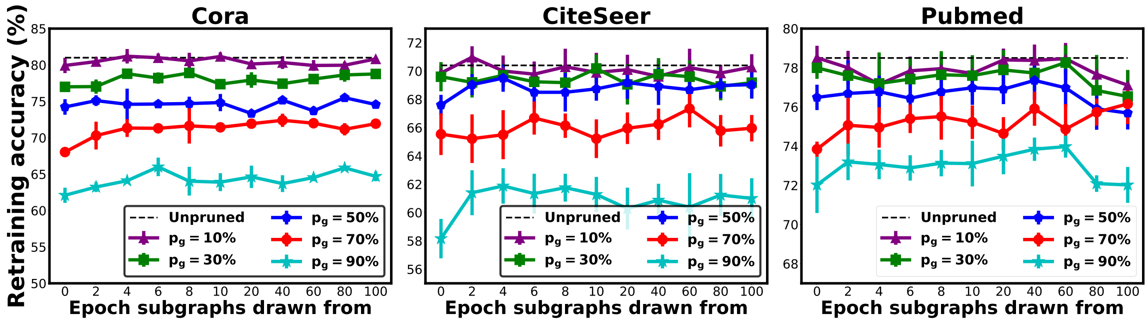


Figure 1: Retraining accuracy vs. epoch numbers at which subgraphs are drawn, when evaluating the GCNs (Kipf and Welling 2017) on three graph datasets: Cora, Citeseer, and Pumbed, where dashed lines show the accuracy of GCNs on corresponding unpruned full graphs, p_g denotes the graph pruning ratios, and error bars show the minimum and maximum of ten runs.

where $\hat{A} = D^{-\frac{1}{2}}(A + I_n)D^{-\frac{1}{2}}$ is calculated by a pre-processing step, thus multiplying $\hat{A}$ captures GCNs' neighbor aggregation; W_0 and W_1 are the weights of the GCN model for the 1st and 2nd layers, e.g., W_0 is an input-to-hidden weight matrix for a hidden layer with H feature maps and W_1 is a hidden-to-output weight matrix with F feature maps (i.e., $Z \in \mathbb{R}^{N\times F}$), where the mapping from the input to the hidden or output layer is called GCN combination which combines each node's features and its neighbors; The softmax function $\text{softmax}(x_i) = \exp(x_i)/\sum_i \exp(x_i)$ is applied in a row-wise manner (Kipf and Welling 2017). For semi-supervised multiclass classification, the loss function of the cross-entropy errors over all labeled examples:

$$\mathcal{L}_{GCN}(W) = -\sum_{n\in\mathcal{Y}_N}\sum_f Y_{nf}\, ln(Z_{nf}), \tag{2}$$

where $\mathcal{Y}_N$ is the set of node indices that have labels, Y_{nf} and Z_{nf} are the ground truth label matrix and the GCN output predictions, respectively. During GCN training, W_0 and W_1 are updated. via gradient descents.

Graph Sparsification. The goal of graph sparsification is to reduce the total number of edges in GCNs' graph (i.e., the size of the adjacency matrices). A SOTA graph sparsification pipeline (Li et al. 2020b) is to first pretrain GCNs on their full graphs, and then sparsify the graphs based on the pretrained GCNs. The weights of GCNs are not updated during graph sparsification, during which W is replaced with A in Eq. (2) to derive the loss function $\mathcal{L}_{GCN}(A)$. The overall loss function during graph sparsification can be written as:

$$\mathcal{L}_{Graph}(A) = \mathcal{L}_{GCN}(A) + \mathcal{L}_{Reg}(A), \tag{3}$$

where $\mathcal{L}_{Reg}$ denotes the sparse regularization term, which ideally will become zero if the sparsity of the graph adjacency matrices reaches the specified pruning ratio (e.g., ${\|A_{prune}\|_0}/{\|A\|_0} \leq 1 - p$ for a given ratio of p). As $\mathcal{L}_{Reg}$ is not differentiable, SOTA graph sparsification work (Li et al. 2020b) formulates Eq. (3) as an alternating optimization problem for updating the graph adjacency matrices.

3.2 Finding 1: EB Tickets Exist in GCN Graphs

In this subsection, we first conduct an extensive set of experiments to show that GEB tickets can be observed across popular graph datasets, and then propose a simple yet effective method to detect the emergence of GEB tickets.

Experiment Settings. For this set of experiments, we follow the SOTA graph sparsification work (Li et al. 2020b) to first *pretrain* GCNs on unpruned graphs, *train and prune* the graphs based on the pretrained GCNs, and then *retrain* GCNs from scratch on the pruned graphs to evaluate the achieved accuracy. In addition, we adopt a two-layer GCN as described in Eq. (1), in which both the GCN and graph training take a total of 100 epochs and an Adam solver is used with a learning rate of 0.01 and 0.001 for training the GCNs and graphs, respectively. For retraining the pruned graphs, we keep the same setting by default.

Existence of GEB Tickets. We follow the SOTA method (Li et al. 2020b) to sparsify the graph, but instead prune the graph that *have not been fully trained* (before the accuracy reaches their final top values), to see if reliable GEB tickets can be observed, i.e., the retraining accuracy reaches the one drawn from the corresponding fully-trained graph. Fig. 1 shows the accuracies achieved by re-training the pruned graphs drawn from different early epochs, considering three different graph datasets and six pruning ratios. **Two intriguing observations** can be made: (1) there consistently exist GEB tickets drawn from certain early epochs (e.g., as early as 10 epochs w.r.t. the total of 100 epochs), of which the retraining accuracy is comparable or even better than those drawn in a later stage, including the "ground-truth" tickets drawn from the fully-trained graphs (i.e., at the 100-th epoch); and (2) some GEB tickets (e.g., $P_g = 30\%$ on Pumbed) can even outperform their unpruned graphs (denoted using dashed lines), potentially thanks to the sparse regularization as mentioned in (You et al. 2020). The first observation implies the possibility of "overcooking" when identifying important graph edges at later training stages.

Detection of GEB Tickets. The existence of GEB tickets and the prohibitive cost of GCN training motivate us to explore the possibility of automatically detecting the emergence of GEB tickets. To do so, we develop a simple yet effective detector via measuring the "graph distance" between consecutive epochs during graph sparsification. Specifically, we define a binary mask of the drawn GEB tickets (i.e., pruned graphs), where 1 denotes the reserved edges and 0 denotes the pruned edges, and use the hamming distance be-

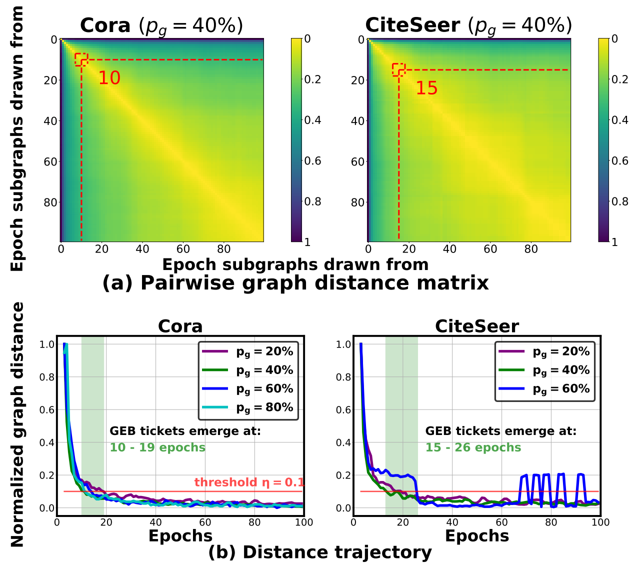


Figure 2: The visualization of (a) pairwise graph distance matrices, and (b) recorded graph distance's evolution along the training trajectories under different graph pruning ratios.

tween the corresponding masks to measure the "distance" between two graphs.

Fig. 2 (a) visualizes the pairwise "graph distance" matrices among 100 training epochs, where the (i, j)-th element within the matrices represents the distance between the pruned graphs drawn at the i-th and j-th epochs. We see that the distance deceases rapidly (i.e., color change from green to yellow) at the first few epochs, indicating that the reserved edges in pruned graphs quickly converge at the very early training stages. We therefore measure and record the distance between consecutive three epochs (i.e., look back for three epochs during training), and stop training the graph when all the recorded distances are smaller than a specified threshold η. Fig. 2 (b) plots the maximum recorded distances as graph training epochs increase, where the red line denotes the threshold we adopt in all experiments with different pruning ratios. The identified GEB tickets are consistently drawn from the early (10- $\sim$ 26-th) epochs. These experiments validate the effectiveness of our developed GEB detector, which has negligible overheads compared with the total graph training cost (i.e., $< 0.1\%$).

3.3 Finding 2: Joint-EB Tickets Exist

In this subsection, we first develop a co-sparsification framework to prune the GCN graphs and networks, and then show in a set of extensive experiments that joint-EB tickets exist across various models and datasets, and then propose a simple detector to detect the emergence of joint-EB tickets during co-sparsification of the GCN graphs and networks.

Co-sparsification of the GCN Graph and Network. To explore the possibility of drawing joint-EB tickects between GCN graphs and networks, we first develop a co-sparsification framework, as described in Fig. 5 (c) and Algorithm 2. Specifically, we iteratively update the GCN weights and graph adjacency matrices based on their corresponding loss functions formulated in Eq. (2) and Eq. (3), respectively; after training for a certain epochs (e.g., 100 epochs), we then simultaneously prune the trained GCN graphs and networks using a magnitude-based pruning method (Han, Mao, and Dally 2015; Frankle and Carbin 2019), and finally retrain the resulting pruned GCNs on the pruned graphs. Fig. 3 shows the accuracy-FLOPS trade-offs of our co-sparsification framework when evaluating GCNs (Kipf and Welling 2017) on Cora and CiteSeer graph datasets. We can see that co-sparsification can achieve up to 90% sparsity in GCN weights while maintaining a comparable accuracy over the unpruned GCN graphs/networks.

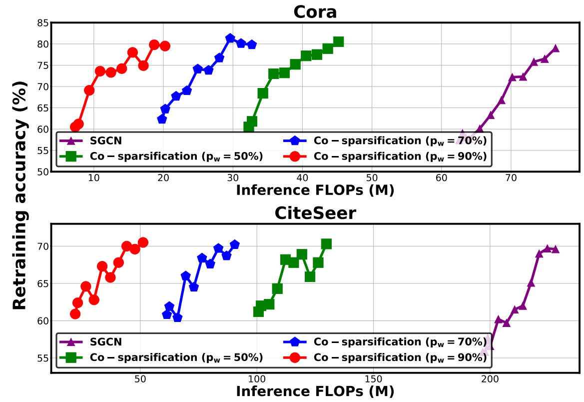
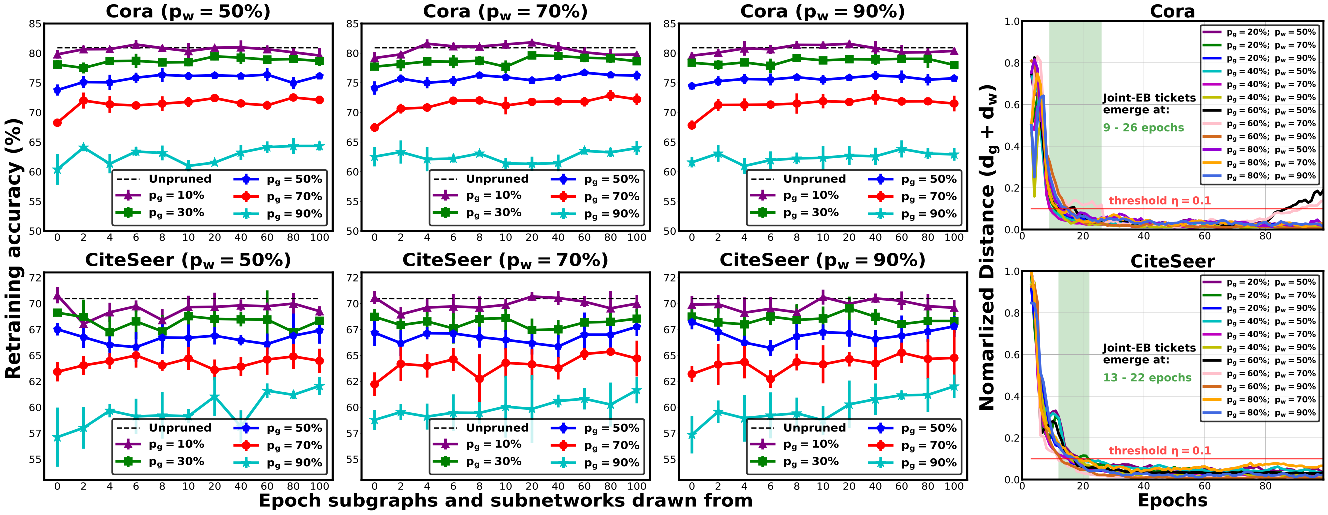


Figure 3: Retraining accuracy vs. inference FLOPs of our co-sparsification framework and a SOTA graph sparsification framework, SGCN (Li et al. 2020b).

Existence of Joint-EB Tickets. The existence of GEB tickets in GCN graphs and EB tickets in DNNs motivate our curiosity on the existence of joint-EB tickets between GCN graphs and networks. Fig. 4 (a) visualizes the retraining accuracies of the GCN subnetworks on subgraphs with both being drawn from different early epochs, which consistently indicates the existence of joint-EB tickets under an extensive set of experiments with different graph datasets, graph pruning ratios, and weight pruning ratios $\{G, p_g, p_w\}$. Furthermore, we can see that the joint-EB tickets emerge at the very early training stages (as early as 10 epochs w.r.t. a total of 100 epochs), i.e., their retraining accuracy is comparable or even better than that of training the corresponding unpruned GCN graphs and networks or training the pruned graphs and unpruned GCN networks (Li et al. 2020b).

Detection of Joint-EB Tickets. We also develop a simple method to automatically detect the emergence of joint-EB tickets, of which the main idea is similar to the GEB tickets detector but with an additional binary mask for drawing the GCN subnetwork. Similarly, in the binary masks, the pruned weights are set to 0 while the kept ones are set to 1, and the distance between subnetworks is characterize using the hamming distance between the corresponding binary masks following (You et al. 2020) but we additionally define a binary mask of the drawn GCN subnetwork, where the pruned weights are 0 while the kept ones are 1. Therefore the distance between subnetworks is represented by the hamming distance between the corresponding binary masks following (You et al. 2020). For detecting the joint-EB tickets, we measure both the "subgraph distance" d_g and "sub-



(a) The existence of Joint-EB tickets **(b) Distance trajectory**

Figure 4: (a) Retraining accuracy vs. epoch numbers at which both the subgraphs and subnetworks (i.e., joint-EB tickets) are drawn, for GCN networks (Kipf and Welling 2017) on Cora and CiteSeer datasets, where p_g indicates the graph pruning ratio and p_w denotes the network pruning ratio, and (b) the distance's evolution along the training trajectories under different graph and network pruning ratio pairs.

network distance" d_w among consecutive epochs, resulting in three choices for the stop criteria (for a given the threshold η): (1) $d_g < \eta$; (2) $d_w < \eta$; (3) $d_g + d_w < \eta$.

Fig. 4 (b) leverages the third criterion to visualize the distance's trajectories of GCN networks on Cora and CiteSeer datasets, at different graph and network pruning ratio pairs $\{p_g, p_w\}$. **The ablation studies of all of the three criteria can be found in the Appendix.** We can see that all criteria can effectively identify the emergence of joint-EB tickets, e.g., as early as 9 epochs w.r.t. a total of 100 epochs. Interestingly, the drawn joint-EB tickets can achieve a comparable or even better retraining accuracy than the subgraph and subnetwork pairs drawn at a later stages, which again implies the possibility of "over-cooking" as in the case of DNNs discussed in (You et al. 2020). All results in this set of experiments consistently validate the existence of joint-EB tickets and the effectiveness of our joint-EB ticket detector.

3.4 Proposed GEBT: Efficient Training+Inference

In this subsection, we present our proposed GEBT technique, which aims to leverage the existence of both GEB tickets and joint-EB tickets to develop a generic GCN efficient training framework. Note that GEBT achieves "win-win": both efficient training and inference as the resulting trained GCN graphs and networks are naturally efficient. Here we will first describe the GEBT technique and then provide a complexity analysis to show GEBT's advantages.

GEBT via GEB Tickets. Fig. 5 (b) illustrates the overall pipeline of the proposed GEBT via drawing GEB tickets. Specifically, GEBT via drawing GEB tickets involves three steps: pretrain GCNs on the full graphs, train and sparsify the graph for identifying GEB tickets, and then retrain the GCN networks on the GEB tickets. The GEB ticket detection scheme is described in Algorithm 1. Specifically, we use a magnitude-based pruning method (Han, Mao, and Dally 2015) to derive the graph mask (i.e., m) for calculating the graph distance between subgraphs from consecutive epochs and then store them into a first-in-first-out (FIFO) queue with a length of $l = 3$; The GEBT training will stop when the maximum graph distance is smaller than a specified threshold η which is set to 0.1 in all our experiments, and return the GEB tickets (i.e., A_p) to be retrained.

GEBT via joint-EB Tickets. Fig. 5 (c) shows the overall pipeline of the proposed GEBT technique via drawing joint-EB tickets. While SOTA efficient GCN training methods consist of three steps: (1) fully pretrain the GCN networks on the full graphs, (2) train and prune the graphs based on pretrained GCNs, and (3) retrain the GCN networks on pruned graph from scratch. Accordingly, here GEBT via drawing joint-EB tickets only has two steps, it first follows the co-sparsification framework as described in previous sections to prune and derive the GCN subgraph and subnetwork pairs, and then retrain the subnetwork on the drawn subgraph to restore accuracies. The joint-EB tickets detection scheme is described in Algorithm 2, where a FIFO queue is adopted for recording both the distance of subgraphs d_g and subnetworks d_w between consecutive epochs. GEBT training will stop when $d_g + d_w$ is smaller than a predefined threshold $\eta = 0.1$, and return the detected joint-EB tickets (i.e., A_p and W_p) for further retraining. Note that the initialization for retraining inherits from joint-EB tickets.

Complexity Analysis of GEBT vs. SOTA Methods. Here we provide complexity analysis to quantify the advantages of our GEBT technique. The time and memory complexity of GCN inferences can be captured by $\mathcal{O}(LMF + LNF^2)$ and $\mathcal{O}(LNF + LF^2)$, respectively, where L, N, M and F are the total number of GCN layers, nodes, edges, and features, respectively. (Chiang et al. 2019). Assuming that drawing joint-EB tickets leads to p_g and p_w sparsities in GCN graphs and networks, respectively, then the inference time and memory complexity of GCNs resulting from our GEBT is $\mathcal{O}((1 - p_g)LMF + (1 - p_w)LNF^2)$ and

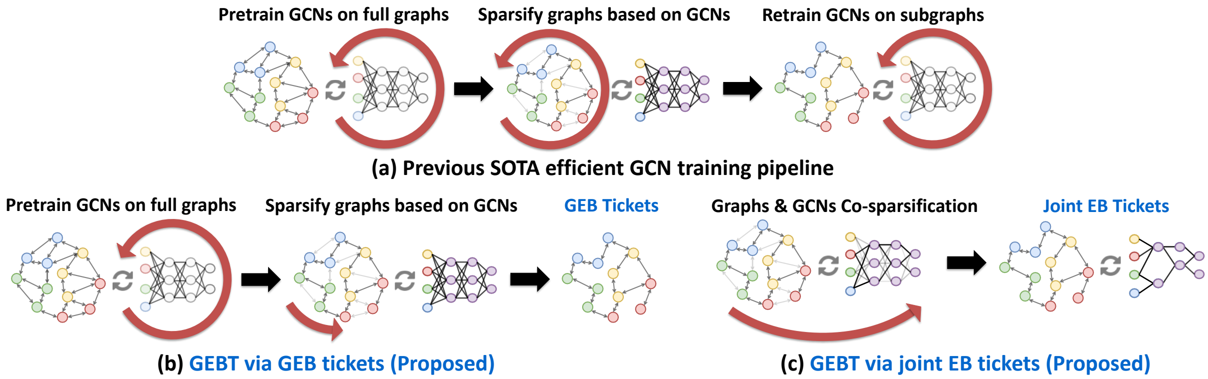


Figure 5: An overview of the existing efficient GCN training pipeline and our GEBT training schemes via drawing GEB tickets and joint-EB tickets (red circle denotes the training process).

Algorithm 1: GEB Tickets Identification

Input: Graph $G = \{V, E, A, X\}$, graph pruning ratio p_g, pretrained GCN weights W, and a FIFO queqe Q with lenght l
Output: The pruned adjacency matrix A_p
while t *(epoch)* $< t_{max}$ **do**
  GCN forward based on Eq. (1)
  Update A based on the $\mathcal{L}_{Graph}$ in Eq. (3)
  Derive graph mask m_t based on A and ratio p_g
  Calculate the graph distance d_g between m_t and m_{t-1} and add to Q
  if ***Max***$(Q) < \eta$ **then**
    $t_{EB} = t$
    Return $A_p = m_t \odot A$
  end
end

$\mathcal{O}(LNF + (1-p_w)LF^2)$, respectively. Note that the corresponding training complexity will be scaled up by the total number of the required training epochs.

4 Experiment Results

4.1 Experiment Setting

Models and Datasets. We evaluate the proposed methods over five representative GCN algorithms, i.e., GCN (Kipf and Welling 2017), GAT (Veličković et al. 2018), GIN (Xu et al. 2019), GraphSAGE (Hamilton, Ying, and Leskovec 2017), and 7/14/28-layer deep ResGCNs (Li et al. 2020a), on three citation graph datasets, i.e., Cora, CiteSeer, and Pubmed (Sen et al. 2008), two inductive datasets, i.e., PPI and Reddit (Hamilton, Ying, and Leskovec 2017), and two large-scale graph datasets from *Open Graph Benchmark (OGB)* (Hu et al. 2020), i.e., Ogbn-ArXiv for node classification and Ogbl-Collab for link prediction. The statistics of these seven datasets are summarized in Tab. 1.

Training Settings. We follow (Kipf and Welling 2017) to train all the chosen two-layer GCN models on the three citation graph datasets and two inductive graph datasets, and follow (Li et al. 2020a) to train ResGCNs on OGB graphs. The detailed training settings are elaborated in the Appendix.

Baselines and Evaluation Metrics. We evaluate the effectiveness of the proposed GEBT's improved training and inference efficiency in terms of the node classification accuracy (or F1 Score, Hits@50), inference FLOPs, and total training FLOPs, as compared to other graph sparsifiers, i.e., random pruning (Frankle and Carbin 2019) and SGCN (Li et al. 2020b), and **ten standard SOTA GCN algorithms** using unpruned graphs.

Algorithm 2: Joint-EB Tickets Identification

Input: Graph $G = \{V, E, A, X\}$, graph and weight pruning ratio p_g and p_w, and a FIFO queqe Q with lenght l
Output: The pruned adjacency matrix A_p and the pruned GCN weights W_p
Initialize the GCN weights W
while t *(epoch)* $< t_{max}$ **do**
  GCN forward based on Eq. (1)
  Update W based on the $\mathcal{L}_{GCN}$ in Eq. (2)
  Update A based on the $\mathcal{L}_{Graph}$ in Eq. (3)
  Derive graph mask m_t and network mask n_t based on A, W and pruning ratio p_g, p_w
  Calculate the distance d_g between m_t and m_{t-1}, d_w between n_t and n_{t-1}, and add $d_g + d_w$ to Q
  if ***Max***$(Q) < \eta$ **then**
    $t_{EB} = t$
    Return $A_p = m_t \odot A$; $W_p = n_t \odot W$
  end
end

4.2 GEBT over SOTA Sparsifiers

We compare the proposed GEBT with existing SOTA GCN sparsification pipelines (Li et al. 2020b) on the three citation graphs to evaluate the effectiveness of GEBT. Fig. 6 shows that GEBT consistently outperforms all competitors in terms of measured accuracies and computational costs (i.e., training and inference FLOPs) trade-offs. Specifically, GEBT via GEB tickets achieves 24.7%∼32.1% training FLOPs reduc-

Table 1: The statistics of the adopted graph datasets.

Dataset	Nodes	Edges	Features	Classes	Metric
Cora	2,708	5,429	1,433	7	Accuracy
Citeseer	3,312	4,732	3,703	6	Accuracy
Pubmed	19,717	44,338	500	3	Accuracy
PPI	56,944	818,716	50	121	F1 Score
Ogbn-ArXiv	169,343	1,166,243	128	40	Accuracy
Ogbl-Collab	235,868	1,285,465	128	2	Hits@50
Reddit	232,965	114,615,892	602	41	F1 Score

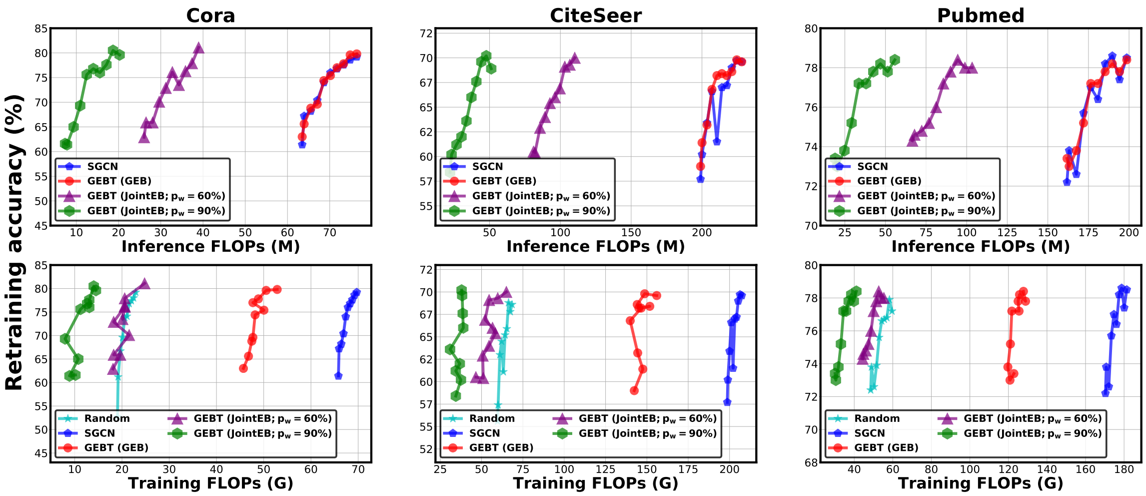


Figure 6: Evaluating the retraining accuracy, training and inference FLOPs of the proposed GEBT over SOTA graph sparsification methods (Random pruning (Frankle and Carbin 2019) and SGCN (Li et al. 2020b)), under different graph and network sparsity pairs. Note that each method has a series of points for representing different graph sparsities ranging from 10% to 90%.

Table 2: GEBT vs. SOTA GCN methods on citation graphs, where ↑ and ↓ denote the improvement over original models.

Methods	Accuracy (%)			Inference FLOPs (M)		
	Cora	CiteSeer	Pumbed	Cora	CiteSeer	Pumbed
GCN	80.9	69.4	79.0	77.95	231.6	203.1
GraphSAGE	82.5	71.0	78.9	6239	19654	15868
GAT	82.1	72.1	79.0	623.6	1853	1624
GIN	81.6	70.9	79.1	77.95	231.6	203.1
GEBT (GCN)	81.1 (↑0.2)	70.5 (↑1.1)	78.5 (↓0.5)	24.9 (↑3.1×)	51.2 (↑4.5×)	55.8 (↑3.6×)
GEBT (GraphSAGE)	82.6 (↑0.1)	70.7 (↓0.3)	78.0 (↓0.9)	624 (↑10×)	1965 (↑10×)	4760 (↑3.3×)
GEBT (GAT)	82.2 (↑0.1)	74.1 (↑2.0)	79.8 (↑0.8)	149 (↑4.2×)	382 (↑4.9×)	446 (↑3.6×)
GEBT (GIN)	82.4 (↑0.8)	71.4 (↑0.5)	79.7 (↑0.6)	20.2 (↑3.8×)	90.5 (↑2.6×)	55.8 (↑3.6×)
Overall Improv.	**↓0.9 ∼ ↑2.0**			**↑2.6× ∼ ↑10.0×**		

Table 3: GEBT vs. SOTA efficient GCN methods on PPI.

Methods	PPI (56K nodes and 818K edges)		
	F1 Scores (%)	Infer. FLOPs (G)	Train. FLOPs (T)
GAT	98.2	3.15	18.9
ResGCN	98.5	47.85	287.1
ClusterGCN	99.3	35.0	210.0
GraphSAGE	61.2	155.8	934.8
VRGCN	97.8	76.75	460.5
GraphSAINT	98.1	35.0	210.0
L2-GCN	96.8	35.0	210.0
N-GCN	65.0	30.42	182.5
GEBT (GAT) vs. GAT	98.8 (↑0.6)	1.84 (↑1.7×)	11.2 (↑1.7×)
GEBT (ResGCN) vs. ResGCN	98.6 (↑0.1)	24.15 (↑2.0×)	147.8 (↑1.9×)
GEBT (ClusterGCN) vs. ClusterGCN	99.2 (↓0.1)	19.31 (↑1.8×)	118.2 (↑1.8×)
Overall Improv.	**↓0.1 ∼ ↑38**	**↑1.7× ∼ ↑84.1×**	**↑1.7× ∼ ↑ 83.5×**

tion while offering comparable accuracies (↓1.4%∼↑4.9%) across a wide range of graph pruning ratios, as compared to SGCN. Furthermore, GEBT via joint-EB tickets even aggressively reaches 80.2%∼85.6% and 84.6%∼87.5% reduction in training FLOPs and inference FLOPs, respectively, over SGCN when pruning the GCN networks up to 90% sparsity, meanwhile leading to a comparable accuracy range (↓1.3%∼↑1.4%). This set of experiments verify (1) the efficiency benefits of the GEBT framework and (2) the high-quality of the drawn GEB tickets and joint-EB tickets.

4.3 GEBT over SOTA GCNs

To evaluate the benefits of GEBT, we first compare the performance of GEBT over four SOTA GCN algorithms on three citation graphs. As shown in Tab. 2, GEBT consistently outperforms all the baselines in terms of efficiency-accuracy trade-offs. Specifically, GEBT achieves 2.6× ∼ 10× inference FLOPs reduction, while offering a comparable accuracy (↓0.9% ∼ ↑2.0%), as compared to SOTA GCN algorithms. We further evaluate GEBT with eight SOTA methods on two large datasets, PPI and Reddit, and show the comparisons in Tables 3 and 4, respectively, where (↑) and (↓) denote improvement over the *original* models, and "Overall Improv." denotes the best improvement over all SOTA baselines. GEBT again consistently achieves the best efficiency-accuracy trade-offs, e.g., reducing inference FLOPs (up to 84.1%) and training FLOPs (up to 83.5%) under comparable or even higher F1-micro scores (↓0.1% ∼ ↑38%).

Table 4: GEBT vs. SOTA efficient GCN methods on Reddit.

Methods	Reddit (232K nodes and 11M edges)		
	F1 Scores (%)	Infer. FLOPs (G)	Train. FLOPs (T)
GCN	95.6	52.3	470.9
GraphSAGE	95.4	2396.7	21570.7
FastGCN	93.7	958.7	8628.3
VRGCN	96.3	956.6	8609.7
ClusterGCN	96.6	226.8	2041.1
GraphSAINT	96.6	226.8	2041.1
GTTF (GraphSAGE)	95.9	2396.7	21570.7
L2-GCN	94.0	226.8	2041.1
GEBT (GCN) vs. GCN	95.8 (↑0.2)	29.3 (↑1.8×)	266.9 (↑1.7×)
GEBT (GraphSAGE) vs. GraphSAGE	97.1 (↑1.7)	1198.4 (↑2.0×)	10929.1 (↑2.0×)
Overall Improv.	**↑0.5 ∼ ↑3.4**	**↑1.8× ∼ ↑81.8×**	**↑1.7× ∼ ↑80.8×**

5 Conclusion

GCNs have gained increasing attention thanks to their SOTA performance on graphs. However, the notorious challenge of GCN training and inference limits their application to large real-world graphs and hinders the exploration of deeper and more sophisticated GCN graphs. To this end, we advocate graph-network co-optimization and explore the possibility of drawing early-bird tickets when sparsifying GCN graphs. Specifically, we for the first time discover the existence of GEB tickets that emerge at the very early stage when sparsifying GCN graphs, and propose a simple yet effective detector to automatically identify their emergence. Furthermore, we develop a generic efficient GCN training framework dubbed GEBT that can significantly boost the efficiency of GCN training and inference by enabling co-sparsification and drawing joint-EB of GCNs. Experiments on various GCN models and datasets consistently validate our GEB finding and the effectiveness of our GEBT.

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