Prompt Tuning on Graph-augmented Low-resource Text Classification

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Abstract—Text classification is a fundamental problem in information retrieval with many real-world applications, such as predicting the topics of online articles and the categories of e-commerce product descriptions. However, low-resource text classification, with no or few labeled samples, presents a serious concern for supervised learning. Meanwhile, many text data are inherently grounded on a network structure, such as a hyperlink/citation network for online articles, and a user-item purchase network for e-commerce products. These graph structures capture rich semantic relationships, which can potentially augment low-resource text classification. In this paper, we propose a novel model called Graph-Grounded Pre-training and Prompting (G2P2) to address low-resource text classification in a two-pronged approach. During pre-training, we propose three graph interaction-based contrastive strategies to jointly pre-train a graph-text model; during downstream classification, we explore handcrafted discrete prompts and continuous prompt tuning for the jointly pre-trained model to achieve zero- and few-shot classification, respectively. Besides, for generalizing continuous prompts to unseen classes, we propose conditional prompt tuning on graphs (G2P2*). Extensive experiments on four real-world datasets demonstrate the strength of G2P2 in zero- and few-shot low-resource text classification tasks, and illustrate the advantage of G2P2* in dealing with unseen classes.

Index Terms—Text classification, graph, low-resource learning, pre-training, prompt.

I. Introduction

Text classification is a fundamental research problem with many important applications in information retrieval. For example, predicting the topics of online articles can help readers easily search and navigate within the website or portal [1], and classifying the category of e-commerce product descriptions enables businesses to structure their inventory efficiently and improve users' search experience [2]. Recent advances in natural language processing (NLP) have achieved remarkable success for text classification, especially when there are large-scale and high-quality labeled data. However, data labeling is often costly and time-consuming, making low-resource classification, in which no or few labeled samples are available, an appealing alternative.

To address low-resource text classification, one approach is to utilize pre-trained language models (PLM) [3], [4], many of which are based on the transformer architecture [5] due to its powerful ability of encoding texts. A PLM can be adapted to different tasks by *fine-tuning* the model parameters to task-specific objectives. While the "pre-train, fine-tune" paradigm

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requires fewer labeled data than traditional supervised learning, it suffers from two drawbacks. Firstly, state-of-the-art PLMs typically have huge model size, *e.g.*, GPT-3 has 175 billion parameters [6], which makes fine-tuning prohibitively expensive [7]. Secondly, fine-tuning still needs a reasonable amount of labeled data due to the gap between pre-training and fine-tuning objectives, and thus struggles with low-resource scenarios including zero- and few-shot classification.

To overcome the problem of pre-training and fine-tuning, prompting [6] has been proposed. It uses a natural language instruction or "prompt" to give a hint of the downstream task, whilst freezing the parameters of a large PLM. In other words, no fine-tuning or additional training is required at all for a new task. However, discrete natural language prompts can be difficult to design and may result in suboptimal performance compared to fine-tuning [8]. More recently, prompt tuning [8], [9] formulates a continuous prompt as a learnable embedding, which is optimized during task adaptation without updating the PLM.

Meanwhile,text data frequently rely on network structures, such as hyperlink/citation networks for online articles or useritem interaction graphs for e-commerce products. These graph structures expose valuable relationships between content or descriptions, aiding low-resource text classification. While current PLMs and prompting do not leverage these relationships, graph neural networks (GNNs) [10] excel in processing graph data. GNNs' message-passing architecture allows for the integration of node features and topological structures, resulting in impressive performance on graphs. Nevertheless, traditional end-to-end training of GNNs heavily relies on abundant taskspecific labels, which motivates self-supervised GNNs [11] using well-designed pretext tasks derived from a label-free graph in a contrastive [12] or generative [13], [14] manner. However, the treatment of text features in GNNs remains rudimentary. A simple bag-of-words representation [15] or aggregation of shallow word embeddings [16] is fed into GNNs as the "initial message", which are further propagated along graph structures. Hence, the modeling of texts is coarse-grained, unable to fully capture the subtle semantic differences and similarities within texts.

Challenges and present work. To overcome the limitations of existing text- and graph-based solutions, we must address three open questions.

Firstly, how do we capture fine-grained textual semantics, while leveraging graph structure information jointly? A naïve approach is to use a language model to generate features from raw texts as input, and then train a GNN. However, in this

way the texts and graph are only loosely coupled, lacking an explicit pairing to complement each other. In this paper, we propose graph-grounded contrastive pre-training, to maximize the alignment between text and graph representations based on three types of graph interaction, namely, text-node, text-summary, and node-summary interactions.

Secondly, how do we augment low-resource text classification given a jointly pre-trained graph-text model? Instead of following the traditional fine-tuning paradigm, we try to "prompt" our jointly pre-trained graph-text model, from which the most relevant structural and semantic information can be located to improve low-resource classification. Without the need to update a large pre-trained model, prompting is also more efficient than fine-tuning. Specifically, we employ discrete prompts in zeroshot classification and continuous prompts in few-shot settings. While discrete prompts are manually crafted in the absence of class labels, continuous prompts can be automatically learned from the few-shot labels through a prompt-tuning process. Prompt-tuning is both data- and computation-efficient owing to the much fewer parameters in a continuous prompt than in the pre-trained model. Furthermore, considering the graph structures between texts, we propose a context-based initialization for prompt tuning, which could provide a more informative starting point than random initialization.

Thirdly, how to generalize continuous prompts to unseen classes? While the continuous prompts can be tuned to fit the seen classes that come with few-shot labeled data, they still cannot generalize to wider unseen classes that have no labeled data. To this end, we propose conditional prompt tuning on graphs (G2P2*), which extends G2P2 by further learning a lightweight neural network to generate for each instance an input-conditioned prompt token (vector). Compared to the static prompt in each task, the conditional prompts dynamically adapt to each instance and are thus less sensitive to class shift [17] in unseen classes.

Contributions. To summarize, we make the following contributions in this work.

- This is the first attempt to pre-train text and graph encoders jointly for low-resource text classification.
- We propose a novel model called Graph-Grounded Pretraining and Prompting (G2P2) with three graph interactionbased constrastive strategies in pre-training, as well as discrete and continuous prompts for downstream zero- and few-shot classification, respectively.
- We further propose G2P2*, a conditional prompt tuning approach to generalize the continuous prompts to wider unseen classes.
- We conduct extensive experiments on four real-world datasets to demonstrate the strength of G2P2 in zero- and few-shot text classification.

A preliminary version of this research paper has been accepted for presentation at SIGIR'2023 conference [18]. We provide a summary of the primary enhancements made in this version. (1) *Introduction*: We restructured Sect. I to emphasize the motivation, challenges and insights involved in generalizing learned prompts to broader unseen classes. (2) *Related Work*: We conducted a more comprehensive and up-to-date review

of graph-based prompting methods in Sect. II. (3) *Proposed Approach*: We enhanced the G2P2 model by introducing G2P2* in Sect. IV-D, through the mechanism of conditional prompt tuning. (4) *Experiments*: Additional experiments were carried out to assess the performance of G2P2* in Sect. V-D, and a detailed analysis of the results was performed.

II. RELATED WORK

Graph neural networks. Inspired by the success of convolutional networks in computer vision, GNNs have emerged to handle non-Euclidean relational data [10], ranging from early semi-supervised models such as GCN [19], GAT [20] and GIN [21], to the more recent self-supervised pre-training paradigm [12]–[14], [22]. Besides their widespread success on graph tasks, they have also been leveraged to improve text-based tasks through knowledge graphs [23] and heterogeneous graphs [24], or multi-modality learning [25]. However, these approaches either employ coarse-grained text treatment, or have decoupled graph and text encoders without fully exploiting the intrinsic relationship between them. Although GLEM [26] integrating both the text and graph structure information with large language models and graph neural networks (GNNs), it is not a good low-resource learner.

Language pre-training and prompting. Pre-trained language models [27] have become the most popular backbone in NLP. While earlier PLMs such as GPT [4], BERT [3], XLNet [28] and RoBERTa [29] still have affordable model size, recent introductions such as T5 [30] and GPT-3 [6] produce massive models with billions of parameters. To avoid the high finetuning cost on these large models, prompting [31] starts to receive more attention in the community. A prompt is a special template to pad the task input, with a goal of extracting useful knowledge from PLMs to flexibly adapt to downstream tasks. Fueled by the success of GPT-3, numerous prompting methods including discrete natural language prompt [32]–[34] and continuous prompt [7]-[9], [35], [36] have emerged. The strength of prompting has been validated in a wide range of NLP applications, including text classification [37]–[41], machine translation [42] and relation extraction [43], [44]. More recently, prompting has also been applied to GNNs for graphcentric tasks such as node classification [45], [46] and graph classification [47], [48], but they cannot utilize fine-grained text information.

Zero- or few-shot paradigms. Broadly speaking, our setting is also related to other learning paradigms. For example, in semi-supervised learning [49]–[51], each class may only have a few examples, but all classes must be seen in training and they cannot handle any novel class during testing. Meta-learning [52]–[60] is another popular paradigm that supports few-shot learning. However, large-scale labeled data are still required in a so-called "meta-training" phase, to support the few-shot learning of novel classes during "meta-testing". In contrast, we only need label-free data for pre-training, without requiring any meta-training phase that would consume large-scale labeled data. Separately, there also exists joint consideration of image and text data using a contrastive pre-training strategy for zero-or few-shot classification [17], [61], [62]. In our work, graph

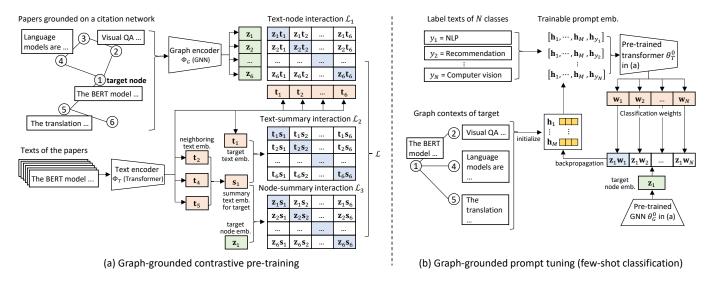


Fig. 1. Overall framework of G2P2. (a) During pre-training, it jointly trains a text and a graph encoder through three contrastive strategies. (b) During testing, it performs prompt-assisted zero- or few-shot classification. Note that part (b) only shows continuous prompt tuning for few-shot classification, while discrete prompts for zero-shot inference and conditional prompt tuning for generalization to wider unseen classes are presented separately in Figs. 2 and 3, repsectively.

data are significantly different from images, which provide various types of interaction between texts. On graphs, zero-shot node classification has also been done [63]. It relies heavily on the availability of Wikipedia pages or other side information to generate class prototype embeddings. However, it is very labor-intensive to find and curate the right side information, especially when there are a large number of classes and/or novel classes emerge frequently.

III. PRELIMINARIES

In this section, we introduce relevant concepts and our low-resource classification settings.

Graph-grounded text corpus. Consider a set of documents \mathcal{D} , which is grounded on a graph $\mathcal{G} = (\mathcal{D}, \mathcal{E}, \mathbf{X})$ such that each document $d_i \in \mathcal{D}$ is a node v_i in the graph. The documents are linked via edges in \mathcal{E} , which are formed based on the application (e.g., if each document represents an article, the edges could be citations between articles). Each node v_i is also associate with a feature vector \mathbf{x}_i , given by the input feature matrix \mathbf{X} . Finally, each document/node¹ has a class label (e.g., the topic of the article).

Low-resource classification. A low-resource task consists of a support set $\mathcal S$ and a query set $\mathcal Q$. The support set $\mathcal S$ contains N classes, and each class has K labeled examples where K is a small number (e.g., 1 or 5), known as N-way K-shot classification. The query set $\mathcal Q$ contains one or more unlabeled instances belonging to the N classes in the support set. Our goal is to classify the instances in the query set based on the labeled examples in the support set. Unlike episodic few-shot meta-learning [52] which has both training tasks and testing tasks, we only have testing tasks; in the training stage, we perform self-supervised pre-training on label-free data only. As a special case, tasks with K=0 are known as zero-shot

¹We will use "node" and "document" interchangeably given their one-one correspondence in our context.

classification, which means there is no labeled example at all and we can only rely on class metadata (e.g., class label text).

IV. PROPOSED APPROACH

In this section, we introduce our novel model G2P2 for low-resource text classification.

A. Overview of G2P2

As shown in Fig. 1, our model G2P2 consists of two stages: (a) graph-grounded constrastive pre-training, and (b) prompt-tuning for low-resource classification.

During pre-training as shown in Fig. 1(a), we learn a dual-modal embedding space by jointly training a text encoder and graph encoder in a self-supervised fashion, since a document also exists as a node on the graph. More specifically, we use a transformer-based text encoder and a GNN-based graph encoder. The transformer takes the text on each node (i.e., document) as the input, and outputs a text embedding vector \mathbf{t}_i for node v_i . On the other hand, the GNN takes the graph and node features as input, and generates a node embedding vector \mathbf{z}_i for node v_i . Subsequently, in the dual-modal embedding space, we align the text and graph representations on the same or related nodes through three contrastive strategies based on different types of interaction on the graph.

In downstream testing, we employ prompting on our jointly pre-trained graph-text model for zero- or few-shot classification. For zero-shot classification, we use handcrafted discrete prompts (Fig. 2) together with the label text. For few-shot classification, we use continuous prompts to pad the label text (Fig. 1(b)). While continuous prompts are effective for a set of *base classes* with some labeled data, they cannot generalize beyond the base classes to wider unseen classes that do not have any labeled data. Hence, we explore conditional prompt tuning and propose G2P2*, which extends our approach by conditioning the continuous prompts on each instance to enhance their generalization to unseen classes.

B. Graph-grounded contrastive pre-training

As shown in Fig. 1(a), the graph-grounded pre-training learns a dual-modal embedding space by jointly training a text encoder and a graph encoder, based on three types of interaction on the underlying graph.

Dual encoders. The text encoder is a transformer [5], which we denote Φ_T . Given a document d_i , the text encoder² outputs the d-dimensional embedding vector of d_i , denoted $\mathbf{t}_i \in \mathbb{R}^d$:

$$\mathbf{t}_i = \Phi_T(d_i; \theta_T),\tag{1}$$

where θ_T represents the parameter set of the transformer. Correspondingly, let $\mathbf{T} \in \mathbb{R}^{|\mathcal{D}| \times d}$ represents the text embedding matrix for all documents.

At the same time, a document d_i is also a node v_i in the graph. We choose a classic GNN called graph convolutional network (GCN) [19] as the graph encoder, denoted Φ_Z . It similarly outputs an embedding vector $\mathbf{z}_i \in \mathbb{R}^d$ for a given node v_i :

$$\mathbf{z}_i = \Phi_Z(v_i; \theta_G), \tag{2}$$

where θ_G represents the parameter set of the GCN. Likewise, let $\mathbf{Z} \in \mathbb{R}^{|\mathcal{D}| \times d}$ represents the graph embedding matrix for all nodes.

Text-node interaction. Our graph-grounded texts naturally implies a bijection between nodes and texts, where each document d_i corresponds to the node v_i in the graph. Inspired by the pairing of image and its caption text [61] and the mapping of content and node sequences [64], we design a pre-training strategy to predict which text document matches which node in the graph.

Specifically, given n documents and the corresponding nnodes, there are n^2 possible document-node pairs $\{(d_i, v_i) \mid$ $i, j = 1, \dots, n$. Among them, only n pairs with i = j are true matching, whereas the remaining $n^2 - n$ pairs are false matching. As our first contrastive strategy, we exploit the bijective interaction between texts and nodes on the graph, to maximize the cosine similarity of the n matching pairs, while minimizing the cosine similarity of the $n^2 - n$ unmatching pairs. To compute the cosine similarity for the n^2 pairs, we first perform a row-wise L2 normalization on embedding matrices T and Z to obtain \tilde{T} and \tilde{Z} , respectively. We then compute a node-text similarity matrix $\Lambda_1 \in \mathbb{R}^{n \times n}$ to capture the pairwise cosine similarity, as follows.

$$\mathbf{\Lambda}_1 = \left(\tilde{\mathbf{Z}}\tilde{\mathbf{T}}^{\top}\right) \cdot \exp(\tau),\tag{3}$$

where $\tau \in \mathbb{R}$ is a trainable temperature parameter to scale the similarity values [61].

REMARK. Although $\Lambda_1 \in \mathbb{R}^{n \times n}$ is a dense matrix, it is constructed in a batch-wise manner for practical implementation. That is, n is not the total number of documents but the relatively small batch size, and thus the overhead is negligible. Λ_2 and Λ_3 will be introduced later following the same treatment.

To formulate the contrastive loss based on the text-node bijective interaction, we adapt the *multi-class N-pair loss* [65],

[66], by considering both the row-wise and column-wise cross entropy loss w.r.t. the row or column index. For instance, the i-th row of Λ_1 represents the similarity scores between node v_i and every document, in which the row index i indicates the ground truth document d_i that matches v_i .

$$\mathcal{L}_1 = \frac{1}{2} \left(CE(\mathbf{\Lambda}_1, \mathbf{y}) + CE(\mathbf{\Lambda}_1^\top, \mathbf{y}) \right), \tag{4}$$

where $\mathbf{y} = (1, 2, \dots, n)^{\mathsf{T}}$ is the label vector for contrastive training, and CE denotes the cross entropy loss applied to the input matrix Λ_1 or Λ_1^{\perp} in a row-wise manner.

Text-summary interaction. Apart from the bijective text-node interaction, we further exploit higher-order interactions on the graph. In particular, each document has a set of neighboring documents defined by graph topology. The neighboring documents can be understood as a summary of the target document given the semantic relatedness between them. For example, on a e-commerce network, the products purchased by a user naturally portray a summary of the user and vice versa. Without loss of generality, we employ a simple mean pooling to generate the summary embedding $\mathbf{s}_i \in \mathbb{R}^d$ as follows.

$$\mathbf{s}_i = \frac{1}{|\mathcal{N}_i|} \sum_{j \in \mathcal{N}_i} \mathbf{t}_j. \tag{5}$$

For efficiency, we only sample a fixed number of neighboring documents to generate the summary. Then, let $\mathbf{S} \in \mathbb{R}^{n \times d}$ denote the summary text embedding matrix for all documents.

Hence, as our second contrastive strategy, we seek to align the text embedding of each document and its corresponding summary text embedding, based on the text-summary interaction derived from graph neighborhood. In other words, we maximize the cosine similarity of the n matching pairs of document and its neighborhood-based summary, while minimizing the cosine similarity of the n^2-n unmatching pairs. Specifically, we first follow Eq. (3) to construct a text-summary similarity matrix $\Lambda_2 \in \mathbb{R}^{n \times n}$:

$$\mathbf{\Lambda}_2 = \left(\tilde{\mathbf{T}}\tilde{\mathbf{S}}^\top\right) \cdot \exp(\tau). \tag{6}$$

Subsequently, we apply the same contrastive loss following Eq. (4), as follows.

$$\mathcal{L}_2 = \frac{1}{2} \left(CE(\mathbf{\Lambda}_2, \mathbf{y}) + CE(\mathbf{\Lambda}_2^\top, \mathbf{y}) \right), \tag{7}$$

Node-summary interaction. The neighborhood-based summary for document d_i also serves as a semantic description of node v_i . Mirroring the text-summary interaction, as our third contrastive strategy, we seek to align the node embedding and its neighborhood-based summary text embedding. In the following, we similarly compute a node-summary similarity matrix $\Lambda_3 \in \mathbb{R}^{n \times n}$, and formulate the corresponding contrastive loss \mathcal{L}_3 .

$$\Lambda_3 = \left(\tilde{\mathbf{Z}}\tilde{\mathbf{S}}^\top\right) \cdot \exp(\tau), \tag{8}$$

$$\mathcal{L}_3 = \frac{1}{2} \left(\text{CE}(\Lambda_3, \mathbf{y}) + \text{CE}(\Lambda_3^\top, \mathbf{y}) \right). \tag{9}$$

$$\mathcal{L}_3 = \frac{1}{2} \left(CE(\mathbf{\Lambda}_3, \mathbf{y}) + CE(\mathbf{\Lambda}_3^\top, \mathbf{y}) \right). \tag{9}$$

Overall pre-training objective. Finally, we integrate the three contrastive losses based on the text-node, text-summary and node-summary interactions. We obtain a pre-trained model

²Technically, the input to the text encoder is a sequence of continuous embeddings; the tokens in a document are first converted to word embeddings.

5

Algorithm 1 Pre-training Procedure of G2P2

```
Require: A graph-grounded text corpus \mathcal{G} = (\mathcal{D}, \mathcal{E}, \mathbf{X}).
Ensure: Pre-trained weights of text encoder \theta_T^0, graph encoder \theta_G^0.
 1: \theta_T^0, \theta_G^0 \leftarrow parameters initialization;
    while not converged do
          sample batches of documents from \mathcal{D};
 3:
 4:
          for each batch do
 5:
               for each node v_i/document d_i in the batch do
                    calculate d_i's text embedding \mathbf{t}_i;
                                                                               ⊳ Eq. (1)
 6:
 7:
                    calculate v_i's node embedding \mathbf{z}_i;
                                                                               ⊳ Eq. (2)
 8:
                    calculate v_i's summary embedding s_i;
                                                                               ⊳ Eq. (5)
 9:
               end for
               calculate the similatity matrices \Lambda_1, \Lambda_2, \Lambda_3; \triangleright Eqs. (3),
10:
     (6), (8)
               calculate the contrastive losses \mathcal{L}_1, \mathcal{L}_2, \mathcal{L}_3;
11:
     Eqs. (4), (7), (9)
                                                                             ⊳ Eq. (10)
12:
               update the overall loss \mathcal{L};
               \theta_T^{\hat{0}}, \theta_G^0 \leftarrow \text{update via backpropagation}
13:
14:
15: end while
16: return \theta_T^0, \theta_G^0
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 $\theta^0 = (\theta^0_T, \theta^0_G)$ consisting of the parameters of the dual encoders, given by

$$\theta^0 = \arg\min_{\theta_T, \theta_G} \mathcal{L}_1 + \lambda(\mathcal{L}_2 + \mathcal{L}_3), \tag{10}$$

where $\lambda \in \mathbb{R}^+$ is a hyperparameter to balance the contribution from summary-based interactions.

The pre-training procedure is outlined in Algorithm 1, which has the following complexity per epoch. Let $|\mathcal{D}|$ be the number of documents, η be the number of neighbors sampled to generate the summary embedding in Eq. (5), and β be the batch size. First, the cost of generating the three types of embeddings (lines 5–8) per epoch is $O(|\mathcal{D}|\eta)$, given that calculating the summary embedding needs go through η neighbors. Second, the cost of calculating the three similarity matrices in each batch is $O(\beta^2)$, and the total cost per epoch is $O\left(\frac{|\mathcal{D}|}{\beta}\beta^2\right) = O(|\mathcal{D}|\beta)$ given $\frac{|\mathcal{D}|}{\beta}$ batches in an epoch. Thus, the overall complexity is $O(|\mathcal{D}|(\eta+\beta))$, which is linear in the number of documents given that η and β are small constants. In our implementation, we set $\eta=3$ and $\beta=64$.

C. Prompting joint graph-text model

After pre-training our graph-text model, it is non-trivial to apply it to low-resource classification. To narrow the gap between pre-training and downstream tasks, the traditional "pre-train, fine-tune" paradigm typically introduces a new projection head for the downstream task, which will be fine-tuned together with the whole pre-trained model. However, under the low-resource setting, it is neither effective nor efficient to update the entire model with a huge number of parameters. Without updating massive PLMs, prompting has recently emerged as a powerful alternative to fine-tuning in NLP [31], although prompting has not been explored for graph-text models with jointly pre-trained structural and textual information.

In this part, we elaborate zero-shot classification using handcrafted discrete prompts, as the absence of labeled data in zero-shot tasks cannot support directly learnable prompts.

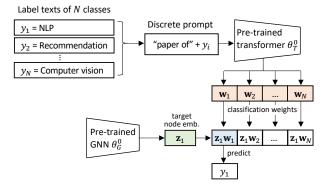


Fig. 2. Schematic diagram for zero-shot classification. The pre-trained models θ_G^0 and θ_T^0 are obtained from Fig. 1(a).

We further discuss automated continuous prompt tuning for few-shot classification.

Discrete prompts for zero-shot classification. In N-way zero-shot classification, out of N classes, we predict the class which has the highest similarity to the given node. As illustrated by the diagram in Fig. 2, the classification weights can be generated by the text encoder based on the class label texts [67], without requiring any labeled sample for the classification task. Specifically, the weight vector \mathbf{w}_y for class $y \in \{1, 2, \dots, N\}$ is the output from the pre-trained text encoder, i.e.,

$$\mathbf{w}_y = \phi_T(\text{"prompt [CLASS]"}; \theta_T^0). \tag{11}$$

Here "prompt [CLASS]" is a prompt template, where [CLASS] refers to the label text of the target class y (e.g., "NLP" for paper area classification), and prompt is a handcrafted sequence of natural language tokens to signal the relevance of the label text (e.g., "paper of NLP" helps focus on the topic of the paper). In the simplest case, prompt can be an empty string so that we only rely on the label text. Note that discrete tokens are still converted to continuous word embeddings as input to the text encoder; for brevity we omit this step in Eq. (11).

Then, the class distribution given node representation \mathbf{z}_i is predicted as

$$p(y \mid \mathbf{z}_i) = \frac{\exp\left(\langle \mathbf{z}_i, \mathbf{w}_y \rangle\right)}{\sum_{y=1}^{N} \exp\left(\langle \mathbf{z}_i, \mathbf{w}_y \rangle\right)},$$
 (12)

where $\langle \cdot, \cdot \rangle$ is cosine similarity.

Continuous prompts for few-shot classification. The problem with discrete prompts is that they are difficult to optimize, given that PLMs are intrinsically continuous. Substituting discrete natural language prompts with learnable continuous prompts, prompt tuning [8], [9], [68] can automate the optimization of prompts when some labeled data is available. Hence, in the few-shot setting, we explore prompt tuning to cue in the relevant structural and semantic information from our jointly pre-trained graph-text model.

Specicifally, instead of a sequence of discrete tokens, we take a sequence of continuous embeddings $[\mathbf{h}_1,\cdots,\mathbf{h}_M,\mathbf{h}_{\text{CLASS}}]$ as the prompt, where M is a hyperparameter indicating the number of context tokens, each \mathbf{h}_m $(m \leq M)$ is a trainable vector, and $\mathbf{h}_{\text{CLASS}}$ is the word embedding sequence of the

target class label. The continuous prompt is fed as input to the text encoder to generate the classification weights for each class y:

$$\mathbf{w}_{y} = \phi_{T}([\mathbf{h}_{1}, \cdots, \mathbf{h}_{M}, \mathbf{h}_{CLASS}]; \theta_{T}^{0}), \tag{13}$$

where each h_m ($m \le M$) has the same dimension as the input word embeddings to the text encoder.

Using the same softmax layer in Eq. (12), we further update the continuous prompt embeddings using the labeled support set of the few-shot task by minimizing a cross entropy loss, whilst freezing the parameters of the dual encoders. This prompt tuning process is both data- and computation-efficient, given the small number of learnable parameters in the prompt.

Furthermore, existing prompt tuning methods either initialize the prompt embeddings randomly [8], [68] or using the word embeddings of handcrafted discrete prompts [62]. While random initialization is non-informative and more prone to local optimum, it is still difficult to pick the right discrete prompts for initialization. Therefore, we take the advantage of graph structures to initialize the prompt embeddings.

Specifically, given a node v_i , we define its graph contexts as its neighbor set $\{v_i \mid j \in \mathcal{N}_i\}$. Due to the underlying semantic relatedness, the graph contexts of the few-shot examples carry strong signals about the task, which can be exploited to improve the initialization. For each document/node v_i in the task support set, we sample η nodes from its graph contexts. For v_i itself and each context node sampled, we truncate its corresponding document to M words, and convert it to a sequence of Mword embedding vectors, each having the same dimension as the vector \mathbf{h}_m ($m \leq M$) in our continuous prompt. Hence, for each support node, we would obtain $\eta+1$ such sequences; in an N-way K-shot task, there is a total of $NK(\eta + 1)$ sequences. We take the average of these embedding sequences to initialize the learnable prompt vectors $\mathbf{h}_1, \dots, \mathbf{h}_M$, which is derived from graph contexts and thus could provide a more informative starting point than random initialization.

D. Conditional prompt tuning: Generalizing continuous prompts to unseen classes

The proposed continuous prompt tuning in Sect. IV-C aims to learn a collection of trainable vectors in each few-shot task. Compared to handcrafted discrete prompts, prompt tuning is automated and tends to be more robust than manual engineering. However, it still requires some labeled data. In particular, prompts learned from some few-shot tasks involving a set of base classes do not generalize well to broader unseen classes. In other words, prompt tuning tends to overfit to the base classes. We hypothesize that this issue originates from the static prompt design, where the prompts, once learned, are tailored specifically to the base classes used during tuning. In contrast, the handcrafted prompts utilized by the zero-shot approach demonstrate a comparatively higher level of generalizability.

To generalize prompt tuning to wider unseen classes, we explore conditional prompt tuning [17]. The core principle is to *condition* a prompt on each individual input instance (*i.e.*, each document/node in our context), rather than learning a static prompt tailed to a specific task or a fixed set of base classes. At

the same time, to ensure parameter efficiency, we extend G2P2 by adding a lean neural network to generate an input-conditional token (vector) for each node, which is then integrated with the learnable prompt vectors. We refer the conditional variant of our method as G2P2*. Intuitively, the conditional token is analogous to node captioning or document summarization, which is equivalent to a description for each node or document. Hence, conditional prompts are more generalizable: They are optimized to depict each instance and thus more resilient to class shift, rather than being confined to certain specific classes.

Recall that in the unconditional version, we learn M global context tokens that can be used with all nodes in a task. In contrast, in the conditional version, we need M context tokens that are specific to each input node. A straightforward approach is to increase the number of parameters, whereby we associate each node with M learnable vectors directly, or train M neural networks to generate M distinct vectors for each node. In either design, the model size is substantially larger than the global context vectors in the original G2P2. Inspired by the Meta-Net architecture [17], [69], we advocate for a more parameterefficient design that has demonstrated impressive results in low-resource settings. Instead, we introduce a light-weight neural network, known as a Meta-Net, on top of the M global context vectors to generates one conditional token (vector) for each input node, which is subsequently merged with the context vectors.

A schematic diagram of the conditional prompt tuning in G2P2* is sketched in Fig. 3. Specifically, our Meta-Net Φ_M employs a dual-layer multi-layer perceptron (MLP) with a bottleneck structure [70]. Given an input node v_i with an embedding vector \mathbf{z}_i , the Meta-Net generates a conditional token π_i , *i.e.*,

$$\pi_i = \Phi_M(\mathbf{z}_i; \theta_M). \tag{14}$$

Then, the *m*-th context vector for node v_i , denoted $\mathbf{h}_{m,i}$, is obtained by

$$\mathbf{h}_{m,i} = \mathbf{h}_m + \pi_i,\tag{15}$$

where \mathbf{h}_m is the m-th global context vector in the original G2P2. Note that the conditional token π_i should have the same dimension as the global context vector \mathbf{h}_m . The conditional prompt for node v_i is thus $[\mathbf{h}_{1,i},\cdots,\mathbf{h}_{M,i},\mathbf{h}_{\text{CLASS}}]$, where $\mathbf{h}_{\text{CLASS}}$ is the word embedding sequence of the target class label identical to that used in the continuous prompt. Subsequently, the conditional prompt is fed as input to the text encoder to output the classification weights, which means the weights are also conditioned on the input node. Specifically, the classification weight for node v_i and class y is

$$\mathbf{w}_{y,i} = \phi_T([\mathbf{h}_{1,i}, \cdots, \mathbf{h}_{M,i}), \mathbf{h}_{\text{CLASS}}]; \theta_T^0).$$
 (16)

Thus, the prediction probability is computed as

$$p(y \mid \mathbf{z}_i) = \frac{\exp\left(\langle \mathbf{z}_i, \mathbf{w}_{y,i} \rangle\right)}{\sum_{y=1}^{N} \exp\left(\langle \mathbf{z}_i, \mathbf{w}_{y,i} \rangle\right)},$$
(17)

During conditional prompt tuning, we update both the global context vectors $\{\mathbf{h}_m\}_{m=1}^M$ and the parameters θ_M of the Meta-Net. Compared to unconditional prompt tuning, the overhead

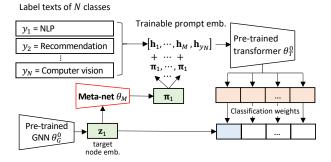


Fig. 3. Schematic diagram for conditional prompt tuning in G2P2*. The pre-trained models θ_G^0 and θ_T^0 are obtained from Fig. 1(a).

only lies in the light-weight Meta-Net with a small set of parameters θ_M .

V. EXPERIMENTS

We conduct extensive experiments to evaluate G2P2³, with comparison to state-of-the-art baselines and model analyses.

A. Experimental setup

Datasets. Four public graph-grounded text corpora are used, as summarized in Tab. I.

- Cora⁴ [71]: known as the "Cora Research Paper Classification" dataset, it is a collection of research papers that are linked to each other through citations. The abstract of a paper is deemed a text document. The papers are classified into a topic hierarchy with 70 leaves. Note that we are using a more comprehensive version of the Cora dataset, which is larger and has more classes than the version used elsewhere [19].
- Art, Industrial and Music Instruments (M.I.)⁵ are three Amazon review datasets [72], respectively from three broad areas, namely, arts, crafts and sewing (Art), industrial and scientific (Industrial), and musical instruments (M.I.). The product descriptions are treated as text documents, while aggregated user reviews form a single document representing individual shopping preferences. Connections between users and products are established through reviews. Fine-grained classification is carried out on product description documents, with product subcategories within a broad area acting as classes. These classes may involve thousands of subtly different categories. User review documents are solely utilized to enhance the semantic understanding of text in relation to the products.

For all datasets, we employ the word2vec algorithm [16] to obtain the 128-dimensional word embeddings of each word in the text documents. Then, for each node, we average the word embedding vectors of all the words in its document, and the averaged vector is used as the node's input features for the GNN-based methods.

TABLE I STATISTICS OF DATASETS.

Dataset	Cora	Art	Industrial	M.I.
# Documents	25,120	1,615,902	1,260,053	905,453
# Links	182,280	4,898,218	3,101,670	2,692,734
# Avg. doc length	141.26	54.23	52.15	84.66
# Avg. node deg	7.26	3.03	2.46	2.97
# Total classes	70	3,347	2,462	1,191

Task construction. We perform zero- or few-shot text classification. We adopt a *5-way* setting, *i.e.*, we sample five classes from all the classes to construct a task. In each task, we construct a K-shot support set by further sampling K examples from each class for $K \in \{0, 1, \ldots, 5\}$, and a validation set of the same size as the support set. The remaining examples form the query set. Note that the support set is labeled and serve as the task training data, whereas the query set is unlabeled and used for evaluation. Note that in our experiment all the classes are used—it is only that each task involves 5 classes, and we have multiple tasks during testing to cover all the classes. This is a typical task setup [52], allowing for a comprehensive evaluation under different class combinations. The reported results are averaged over all the tasks on each dataset.

Baselines for few-shot classification. We consider competitive baselines from four categories.

- (1) *End-to-end GNNs*, which are graph neural networks trained in a supervised, end-to-end manner from random initialization.
- GCN [19]: an variant of convolutional neural network and operates on the graph only.
- SAGE_{sup} [73]: the supervised version of GraphSAGE, an inductive GNN which generates node embeddings by sampling and aggregating features from a node's local neighborhood.
- TextGCN [74]: a GCN-based model on a text graph constructed from word co-occurrence and document-word relations, which jointly learns the embeddings of both words and documents.
- (2) Pre-trained/self-supervised GNNs, these GNNs are pretrained using pretext tasks without labeled data, followed by fine-tuning or fitting a classification head while freezing the model parameters.
- GPT-GNN [14]: a GNN pre-training approach by a self-supervised graph generation task, including node attribute generation and edge generation. It follows the "pre-train, fine-tune" paradigm.
- DGI [12]: a GNN pre-training approach which maximizes the mutual information between local- and global-level representations. As an unsupervised method, it also freezes the model parameters and fits a simple logistic regression model for the downstream few-shot classification, after pretraining.
- SAGE_{self} [73]: the self-supervised version of GraphSAGE, encouraging similar embeddings for neighboring nodes and distinct embeddings for non-adjacent nodes. After pretraining, it follows the same approach of DGI for the downstream classification.

³Code and data: https://github.com/WenZhihao666/G2P2-conditional.

⁴https://people.cs.umass.edu/~mccallum/data.html

⁵http://deepyeti.ucsd.edu/jianmo/amazon/index.html

TABLE II
<i>Five-shot</i> Classification performance (percent) with 95% confidence intervals.

In each column, the best result amo	ong all methods is bolded and the best am	nong the baselines is underlined.	Improvement by G2P2 is calculated
relative to the best baseline. '	indicates that our model significantly out	tperforms the best baseline base	d on two-tail t-test $(p < 0.05)$.

	Co	ora	A	rt	Indu	strial	M.	I.
	Accuracy	Macro-F1	Accuracy	Macro-F1	Accuracy	Macro-F1	Accuracy	Macro-F1
GCN SAGE _{sup} TextGCN	41.15±2.41 41.42±2.90 59.78±1.88	34.50±2.23 35.14±2.14 55.85±1.50	22.47±1.78 22.60±0.56 43.47±1.02	15.45 ± 1.14 16.01 ± 0.28 32.20 ± 1.30	21.08±0.45 20.74±0.91 53.60±0.70	15.23±0.29 15.31±0.37 45.97±0.49	22.54±0.82 22.14±0.80 46.26±0.91	16.26±0.72 16.69±0.62 38.75±0.78
GPT-GNN DGI SAGE _{self}	$\begin{array}{c c} 76.72 \pm 2.02 \\ \underline{78.42} \pm 1.39 \\ \overline{77.59} \pm 1.71 \end{array}$	72.23 ± 1.17 74.58 ± 1.24 73.47 ± 1.53	65.15±1.37 65.41±0.86 76.13±0.94	52.79 ± 0.83 53.57 ± 0.75 65.25 ± 0.31	62.13±0.65 52.29±0.66 71.87±0.61	54.47±0.67 45.26±0.51 65.09±0.47	67.97±2.49 68.06±0.73 77.70±0.48	59.89 ± 2.51 60.64 ± 0.61 70.87 ± 0.59
BERT BERT* RoBERTa RoBERTa*	37.86±5.31 27.22±1.22 62.10±2.77 67.42±4.35	32.78±5.01 23.34±1.11 57.21±2.51 62.72±3.02	46.39±1.05 45.31±0.96 72.95±1.75 74.47±1.00	37.07 ± 0.68 36.28 ± 0.71 62.25 ± 1.33 63.35 ± 1.09	54.00±0.20 49.60±0.27 76.35±0.65 77.08±1.02	47.57±0.50 43.36±0.27 70.49±0.59 71.44±0.87	50.14±0.68 40.19±0.74 70.67±0.87 74.61±1.08	42.96 ± 1.02 33.69 ± 0.72 63.50 ± 1.11 67.78 ± 0.95
P-Tuning v2	71.00±2.03	66.76±1.95	76.86 ± 0.59	<u>66.89</u> ±1.14	<u>79.65</u> ±0.38	74.33±0.37	72.08±0.51	65.44±0.63
G2P2-p G2P2 (improv.)	79.16±1.23 80.08 *±1.33 (+2.12%)	74.99±1.35 75.91 *±1.39 (+1.78%)	79.59±0.31 81.03 *±0.43 (+5.43%)	68.26±0.43 69.86*±0.67 (+4.44%)	80.86±0.40 82.46*±0.29 (+3.53%)	74.44±0.29 76.36 *±0.25 (+2.7%)	81.26±0.36 82.77 *±0.32 (+6.53%)	74.82±0.45 76.48 *±0.52 (+7.92%)

- (3) Pre-trained transformers, which are pre-trained using masked language modeling, and then are fine-tuned together with a randomly initialized classification head (e.g., a fully connected layer), for the downstream few-shot classification task.
- BERT [3]: a pre-trained transformer which pre-trains the transformer using masked language modeling, *i.e.*, during training, output deep bidirectional representations from unlabeled text by jointly conditioned on both left and right context in all layers.
- RoBERTa [29]: a replication of BERT that carefully measures the impact of many key hyperparameters and training data size during training.
- BERT* and RoBERTa*: variants of BERT and RoBERTa, which are obtained by fine-tuning the pre-trained BERT and RoBERTa, respectively, using masked language modeling on our datasets, to mitigate the domain gap between our datasets and the datasets used for pre-training BERT and RoBERTa.
- (4) *Prompt tuning*: P-Tuning v2 [68], is a version of prefixtuning [7] optimized and adapted for natural language. It uses deep prompt tuning, which applies continuous prompts for every layer of the pre-trained language model.

Note that our setting is distinct from few-shot learning under the meta-learning paradigm [52], as there is no few-shot tasks for the meta-training phase. Hence, we cannot use state-of-the-art meta-learning models for comparison. Besides, two of the baselines we compared, DGI and SAGE_{self}, have adopted a form of linear probe which is known to be a strong few-shot learner [75].

Baselines for zero-shot classification. We only compare with PLMs, as all the other methods require at least one shot to work. For each method, we use the discrete prompt [CLASS] (i.e., the label text alone). We also evaluate handcrafted prompts "prompt [CLASS]", where prompt is a sequence of tokens found by prompt engineering, and annotate the model name

with "+d". Essentially, we compute the similarity between the target document and the label text of each class (with or without additional tokens), and predict the most similar class following Fig. 2.

Parameter settings. For G2P2, the text encoder is a transformer [5]. Following CLIP [61], we use a 63M-parameter, 12-layer 512-wide model with 8 attention heads. It operates on a lowercased byte pair encoding (BPE) representation of the texts with a 49,152 vocabulary size [76]. The max sequence length is capped at 128. The graph encoder employs a GCN [19], using two layers [73] with a LeakyReLU activation, each with 128 dimensions [77]. The pre-training of our model starts from scratch without initializing the graph and text encoders with previously pre-trained weights. λ in Eq. (10) is set to 0.1 on Cora, and set to 10 on the three amazon review datasets, which were chosen from $\{0.01, 0.1, 1, 10, 100\}$ according to the accuracy on validation data. The number of learnable prompt tokens, M in Eq. (13), is set to 4, which was chosen from $\{2,$ 4, 8, 16, 32} according to the accuracy on validation data. We use the Adam optimizer with the learning rate 2×10^{-5} with 2 training epochs, and a batch size of 64 in pre-training, referring to Hugging Face's [78] example settings. The text embedding size is 128, same to the output from the graph encoder. To generate the summary embedding and the context-based prompt initialization, the number of neighboring nodes sampled is 3. For prompt tuning, we set the learning rate as 0.01, which was chosen from $\{0.0001,0.001,0.01,0.1\}$ according to the accuracy on validation data. For the Meta-Net of G2P2*, we employ a two-layer MLP and set hidden dimensions as 8 and 512 using ReLU activation.

For all the GNN methods, including the GNN component in G2P2, we use the 128-dimensional word2vec embeddings [16] of raw texts as the input node features. We use a two-layer architecture, and set the hidden dimension to be 128, except for GCN and $SAGE_{sup}$ whose hidden dimension is set to 32 [19] which gives better empirical performance. For all GNN pre-

training baselines, we use 0.01 as the learning rate. For BERT, RoBERTa and G2P2, we adopt 0.00002 as the learning rate. Our implementations of BERT, RoBERTa and their masked language modeling are based on Hugging Face's transformers [78]. For both BERT and RoBERTa, we use their base versions, given that our model G2P2 uses just a small 63M-parameter model, following previous work [61]. For P-Tuning v2, we use the original code on the RoBERTa backbone, and take the recommended 0.005 as the learning rate for prompt tuning. For G2P2, the learning rate for prompt tuning is set to 0.01.

We conduct all experiments on a server with 4 units of GeForce RTX 3090 GPU. Pre-training G2P2 takes about 0.5/6/9/10 hours on Cora/M.I./Industrial/Art, respectively, on a single GPU. The inference (with prompt tuning) is conducted with five different splits generated from five random seeds {1, 2, 4, 8, 16}.

B. Performance of G2P2

We evaluate the classification performance under various shots.

Five shots. In Tab. II, we first compare the performance of G2P2 with baselines under the *5-shot* setting. G2P2 emerges as the winner consistently, outperforming the best baseline by around 2–8% with statistical significance.

We also make a few more observations. Firstly, among the GNNs, pre-trained/self-supervised models tend to perform better than the end-to-end approaches, since the latter heavily rely on labeled data. Among the former, DGI and SAGE_{self} perform better as they are a form of linear probe, known to be a strong few-shot learner [75]. Note that, instead of using word2vec embeddings [16] of raw texts as node features, we also tired using the pre-trained RoBERTa [29] to generate the node features for DGI and SAGE_{self}. However, doing so does not bring any improvement, showing that it is ineffective to simply combine a language model and GNN in a decoupled manner. In contrast, our proposed model jointly learns the text and graph encoders through three graph-grounded contrastive strategies. Secondly, PLMs are generally superior to GNNs, illustrating the importance of leveraging texts in a fine-grained way. Additionally, RoBERTa outperforms BERT owing to an improved pre-training procedure [29]. However, further training PLMs on our texts gives mixed results: RoBERTa* slightly outperforms RoBERTa but BERT* is much worse than BERT. That means it is not straightforward to mitigate the domain gap by simply continuing training on the domain texts. Thirdly, the continuous prompt approach P-Tuning v2 achieves competitive results compared to fine-tuning, while having the advantage of being much cheaper than fine-tuning. Nevertheless, it is still significantly outperformed by our model G2P2. Furthermore, G2P2-p without prompt tuning is inferior to G2P2, showing the benefit of continuous prompts.

Fewer shots. In addition to the 5-shot setting, in Fig. 4 we also study the impact of fewer shots on G2P2 and several representative baselines. G2P2 generally performs the best across different shots. In general, the performances of all approaches degrade as fewer shots become available. However, the baselines suffer significantly under extreme low-resource

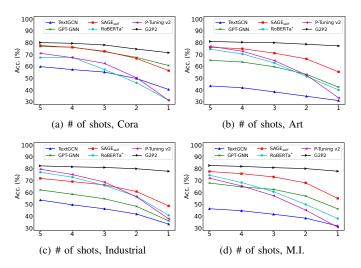


Fig. 4. Performance on different shots.

(e.g., 1- or 2-shot) settings. In contrast, G2P2 remains robust, reporting a relatively small decrease in performance even with just 1 or 2 shots.

The results demonstrate the practical value of our proposed model especially when labeled data are difficult or costly to obtain in time. On the other hand, traditional approaches constantly face the challenge of the inability to keep up with the rapid growth of emerging classes in dynamic and open environments [63]. For example, labeling a large volume of texts for novel topics in online articles, or new product categories in open-ended e-commerce platforms, can suffer a substantial time lag.

Zero shot. Finally, we report the zero-shot performance in Tab. III, where our models G2P2 and G2P2+d significantly outperforms the baselines. The results particularly demonstrate the effectiveness of our graph-grounded contrastive pre-training in the absence of labeled data, which is crucial to handling evolving classes without any labeled sample in many real-world scenarios. Moreover, handcrafted discrete prompts (*i.e.*, BERT*+d and G2P2+d) can be superior to using label text only (*i.e.*, BERT* and G2P2), showing the effectiveness of additional prompt tokens.

However, finding the optimal discrete prompts often requires significant engineering work. Specifically, for the three approaches with discrete prompts, namely, RoBERTa*+d, BERT*+d and G2P2+d, we explored more than 10 handcrafted prompt templates on each dataset, as shown in Tabs. IV-VII, which are typically relevant to the corresponding dataset and require some domain knowledge to devise. While discrete prompts are generally helpful to zero-shot classification, their effectiveness varies. In Tab. III, we simply report the performance of the best handcrafted template for each approach and each dataset. Besides, it is worth noting that the same prompt can sometimes generate opposite results on different models. For instance, in Cora dataset, while "a model of [CLASS]" is the best prompt for RoBERTa*+d, it is a bad choice for G2P2+d. Moreover, some prompts without any semantic meaning, like "a [CLASS]", can be the best choice sometimes. The observations imply that prompt engineering

TABLE III

Zero-shot CLASSIFICATION ACCURACY (PERCENT).

(See Table II for explanations on entry styles.)

	Cora	Art	Industrial	M.I.
RoBERTa	30.46±2.01	42.80±0.94	42.89±0.97	36.40±1.20
RoBERTa*	39.58 ± 1.26	34.77 ± 0.65	37.78 ± 0.32	32.17 ± 0.68
RoBERTa*+d	45.53 ± 1.33	36.11±0.66	39.40 ± 1.22	37.65 ± 0.33
BERT	23.58 ± 1.88	35.88 ± 1.44	37.32 ± 0.85	37.42 ± 0.80
BERT*	23.38 ± 1.96	54.27±1.85	56.02 ± 1.22	50.19 ± 0.72
BERT*+d	26.65 ± 1.71	56.61 ± 1.76	55.93±0.96	52.13 ± 0.88
G2P2	64.75±2.62	76.62±0.53	76.43±0.29	74.44±0.56
G2P2+d	66.43 *±2.82	76.95 *±0.54	77.31 *±0.24	75.94 *±0.62
(improv.)	(+45.90%)	(+35.93%)	(+38.00%)	(+45.67%)

TABLE IV $\label{eq:table_prompt} \textbf{PROMPT ENGINEERING IN ZERO-SHOT TASKS ON CORA. }$

Handcrafted prompt	RoBERTa*+d	BERT*+d	G2P2+d
[CLASS]	39.58±1.26	23.38±1.96	64.75±2.62
a [CLASS]	41.20±1.19	22.96 ± 1.40	66.43 ±2.82
an [CLASS]	40.93 ± 0.86	21.50 ± 1.42	65.64±3.03
of [CLASS]	36.13±1.27	22.85 ± 1.10	65.99±3.20
paper of [CLASS]	35.14±1.14	26.65 ±1.71	63.15±2.36
research of [CLASS]	40.73 ± 1.84	24.61 ± 1.85	63.29±2.96
a paper of [CLASS]	42.20±2.55	21.96 ± 0.93	62.13 ± 3.00
a research of [CLASS]	42.22±2.35	24.25 ± 2.40	61.24±2.30
a model of [CLASS]	45.53 ±1.33	22.42 ± 0.70	61.51±2.90
research paper of [CLASS]	37.83±2.28	26.23±2.28	60.71 ± 2.26
a research paper of [CLASS]	42.01±2.51	22.34±0.62	61.01±2.02

involves labor-intensive work, and the outcomes contain much uncertainty on what would be the optimal discrete prompt. Hence, using the label text only is still a reasonably good choice.

C. Model analyses of G2P2

We conduct more in-depth studies on G2P2. Unless otherwise stated, we report the classification *accuracy* under the *5-shot* setting.

Ablation study. We first evaluate the contribution from each of the three graph interaction-based contrastive strategies, by employing different combinations of the proposed loss terms $\mathcal{L}_1, \mathcal{L}_2$ and \mathcal{L}_3 . As shown in Tab. VIII, strategies without \mathcal{L}_1 have performed quite poorly, demonstrating that the bijective text-node interaction is the fundamental component of our pre-training. That being said, when further adding \mathcal{L}_2 or \mathcal{L}_3 to \mathcal{L}_1 , we still observe a noticeable performance improvement, showing the benefit of incorporating additional graph-based interactions for text data. Lastly, G2P2 with all three loss terms outperforms all 1- or 2-combinations of the losses, demonstrating that the three contrastive strategies are all useful and they are well integrated. Overall, the results reveal that graph information is vital to low-resource text classification, since graph structures reveal rich relationships between documents.

Next, we evaluate the contribution from our prompt-tuning approach. Specifically, we compare G2P2 with two ablated variants: using label text only without trainable prompt vectors, and randomly initializing the prompt vectors. As reported in Tab. VIII, only using label text clearly degrades the classification performance, implying the importance of learning

TABLE V
PROMPT ENGINEERING IN ZERO-SHOT TASKS ON ART.

Handcrafted prompt	RoBERTa*+d	BERT*+d	G2P2+d
[CLASS]	34.77±0.65	54.27±1.85	76.62±0.53
a [CLASS]	26.18±1.07	55.31±1.64	76.95 ±0.54
an [CLASS]	23.98±2.33	56.61 ±1.76	76.89 ± 0.54
of [CLASS]	24.09±1.59	48.25±2.39	76.87 ± 0.70
art [CLASS]	22.00±0.95	55.74±1.59	75.85 ± 0.81
sewing [CLASS]	33.30±1.17	52.20 ± 1.42	76.26 ± 0.60
art of [CLASS]	19.92±1.62	52.45±1.58	75.84 ± 0.79
sewing of [CLASS]	36.11 ±0.66	48.72±1.71	76.41 ± 0.64
arts crafts of [CLASS]	22.42±2.01	49.94±2.13	75.24 ± 0.94
arts crafts or sewing of [CLASS]	21.29±1.92	48.06±1.73	74.32±1.14
an arts crafts or sewing of [CLASS]	21.19±1.03	52.97±1.60	74.08±1.11

TABLE VI PROMPT ENGINEERING IN ZERO-SHOT TASKS ON INDUSTRY.

Handcrafted prompt	RoBERTa*+d	BERT*+d	G2P2+d
[CLASS]	37.78±0.32	56.02 ±1.22	76.43±0.29
a [CLASS]	22.96±0.65	55.72±0.86	76.58 ± 0.25
an [CLASS]	22.72±0.59	55.33±0.86	76.95 ± 0.20
of [CLASS]	27.27 ± 0.22	51.03±0.71	76.50 ± 0.32
industrial [CLASS]	32.56 ± 0.34	54.77±0.96	76.46 ± 0.27
scientific [CLASS]	39.40 ±1.22	53.90±1.08	76.45 ± 0.30
an industrial [CLASS]	23.79 ± 0.43	55.33±0.89	77.21 ± 0.19
a scientific [CLASS]	21.19 ± 0.54	53.10±0.96	76.85 ± 0.25
industrial and scientific [CLASS]	36.72 ± 0.60	53.30±1.04	77.01 ± 0.16
an industrial and scientific [CLASS]	24.83 ± 0.35	52.89 ± 1.02	77.31 ± 0.24
of industrial and scientific [CLASS]	32.96±0.73	49.63±0.82	76.96 ± 0.23

continuous prompts via prompt tuning. Furthermore, our approach G2P2 with context-based initialization for prompt vectors shows a small but consistent advantage over random initialization, implying the usefulness of considering graph structures in prompt tuning.

Hyperparameter study. We first investigate the impact of the interaction coefficient λ in Fig. 5(a), which balances the high-order contrastive losses $(\mathcal{L}_2, \mathcal{L}_3)$. The performance is generally better and stable when λ is slightly bigger $(e.g., \geq 10)$, indicating the significance of the high-order text-summary and node-summary interactions. Next, we study the prompt length M in Fig. 5(b), which refers to the number of trainable prompt vectors in Sect. IV-C. The performance is relatively unaffected by the prompt length, and thus it is robust to choose a small M (e.g., 4) for efficiency.

Efficiency of prompt tuning. In our work, the continuous prompts are optimized by prompt tuning [62], [68] without updating the pre-trained model. In this experiment, we investigate the prompt tuning efficiency of G2P2 in comparison to the efficiency of traditional fine-tuning. As G2P2 has a transformer

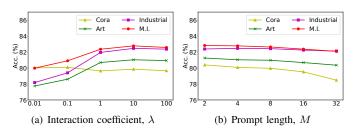


Fig. 5. Hyperparameter study.

TABLE VII
PROMPT ENGINEERING IN ZERO-SHOT TASKS ON M.I.

Handcrafted prompt	RoBERTa*+d	BERT*+d	G2P2+d
[CLASS] a [CLASS] an [CLASS] of [CLASS] instrument [CLASS] musical [CLASS]	$\begin{vmatrix} 32.17 \pm 0.68 \\ 22.48 \pm 1.38 \\ 21.70 \pm 2.17 \\ 22.14 \pm 0.93 \\ 25.24 \pm 0.83 \\ 34.55 \pm 1.03 \end{vmatrix}$	50.19 ± 0.72 51.82 ± 0.60 51.05 ± 0.59 44.64 ± 0.22 47.72 ± 0.63 49.93 ± 0.48	74.44±0.56 75.22±0.62 74.90±0.62 75.09±0.56 75.13±0.52 75.94 +0.62
an instrument [CLASS] a musical [CLASS] an instrument of [CLASS] musical instrument of [CLASS] a musical instrument of [CLASS]	21.57±0.90 20.52±0.78 24.16±1.08 37.65 ±0.33 31.21±0.45	50.94±0.93 52.13 ±0.88 52.02±0.78 48.70±0.80 48.78±0.84	73.95 ± 0.61 75.73 ± 0.74 74.40 ± 0.49 75.33 ± 0.61 75.21 ± 0.88

TABLE VIII
ABLATION STUDY.

	Cora	Art	Industrial	M.I.
Only \mathcal{L}_3	74.66±1.80	52.56±1.09	45.97±0.81	49.05±0.54
Only \mathcal{L}_2	77.01±1.30	58.90±0.55	52.99±0.46	59.41±0.85
Only \mathcal{L}_1	79.50 ± 1.19	77.37 ± 0.72	78.10 ± 0.34	79.70±0.56
\mathcal{L}_2 + \mathcal{L}_3	70.04 ± 2.89	49.91±1.57	50.07 ± 0.50	56.14±1.01
\mathcal{L}_1 + \mathcal{L}_3	79.73 ± 0.89	78.60 ± 0.40	79.97 ± 0.43	80.42±0.45
\mathcal{L}_1 + \mathcal{L}_2	79.42 ± 1.04	80.55±0.52	81.06±0.33	82.39±0.41
Only label text	79.16±1.23	79.59±0.31	80.86±0.40	81.26±0.36
Random init.	80.03±0.99	80.85±0.43	82.43±0.33	82.64±0.21
G2P2	80.08 ±1.33	81.03 ±0.43	82.46 ±0.35	82.77 ±0.32

component, we compare it with four transformer based models, all of which follow the classical "pre-train, fine-tune" paradigm.

As shown in Tab. IX, "Tuning time per task" refers to the average time required per task for prompt tuning by G2P2 or fine-tuning by the baselines, while "Param. size" refers to the number of parameters that require updating. The results demonstrate that prompt tuning in G2P2 is much more efficient than fine-tuning in the baselines, achieving 2.1~18.8x speedups. The reason is that prompt tuning updates far fewer parameters. In G2P2, we used 4 trainable 512-dimensional prompt vectors, totalling to 2048 parameters only, while fine-tuning in the baselines needs to update the whole pre-trained model with more than 100M parameters. Note that the speedup is not

TABLE IX
TUNING TIME AND PARAMETER SIZE.

	Tu	Tuning time per task (in seconds)				
	Cora	Art	Industrial	M.I.	size	
RoBERTa	45.47±2.38	64.22±3.62	43.46±2.99	44.99±2.58	123M	
RoBERTa*	39.38±2.01	59.56±3.55	35.10±2.75	38.84±2.39	123M	
BERT	32.23 ± 1.71	51.77±2.00	31.72±1.77	33.55±2.39	110M	
BERT*	34.82±1.68	55.16±2.32	31.11±1.74	29.00±2.23	110M	
G2P2	2.42 ±0.41	22.03 ±1.39	14.63 ±1.26	12.72 ±1.17	2048	

 $\label{eq:table_X} \textbf{TABLE X}$ Inductive performance on text classification.

	Art	Industrial	M.I.
BERT* RoBERTa*	43.66±0.90 69.55±1.14	48.35±0.25 73.65±0.86	39.24±0.88 71.96±1.44
G2P2	79.81 ±0.22	81.29 ±0.32	81.85 ±0.33

linear w.r.t. the parameter size, due to overheads in the data loader and the optimizer. Overall, our prompt tuning is not only effective under low-resource settings, but also parameterand computation-efficient.

Inductive ability. Our previous experiments can be deemed transductive as both the pre-training of text encoder and downstream text classification are conducted on the whole corpus. To further evaluate the generalization ability of our model, we adopt an "inductive" setting, whereby we pre-train the text encoder only on a subset of the corpus and perform downstream classification on a disjoint subset. Particularly, in the three Amazon datasets, since user texts have no labels and item texts have labels, it is natural for us to pre-train with only user texts and classify only item texts downstream. We also employ masked language modeling on only the user texts for BERT and RoBERTa, to get BERT* and RoBERTa*. As shown in Tab. X, G2P2 still performs very well in the inductive setting, illustrating the strong generalization ability of our pre-trained model.

D. Performance and analyses of G2P2*

Finally, we conduct additional experiments to investigate the performance of G2P2*, in particular the generalization ability of conditional prompt tuning to handle wider unseen classes. In these experiments, on each dataset we randomly sample some (35 for Cora, 66 for Art, 41 for Industrial, 35 for M.I.) classes as the base classes, and the same number of classes as unseen classes. Each base class has 5 labeled instances (5-shot) for selecting or tuning the optimal prompts, and the remaining instances for testing. In contrast, all instances of each unseen class are for testing, without any labeled data for learning. We compare the three variants of our proposed model: (1) G2P2+d, the zero-shot method with handcrafted discrete prompts chosen based on the base classes; (2) G2P2, which learns continuous and static prompts from the base classes; (3) G2P2*, which learns conditional prompts on the base classes.

Generalizing from base to unseen classes. We report the results on the testing sets of both the base classes and unseen classes in Tab. XI. Note that the base and unseen classes come from the same domain, or more specifically the same dataset in our context. Specifically, on the base classes, G2P2+d performs the worst in all cases, showing that the discrete prompts are difficult to optimize for intrinsically continuous PLMs. In contrast, G2P2 generally obtains the best performance on the base classes, showing that continuous prompt tuning can find better prompts if some labeled data are available for tuning. However, the learned static prompts do not generalize well to the unseen classes, showing a significant class shift between base and unseen classes. Interestingly, G2P2+d performs better on unseen classes than G2P2, showing that the handcrafted prompts are robust to class shift to some extent. Overall, in comparison to G2P2+d and G2P2, G2P2* demonstrates competitive performance on the base classes and excellent performance on the unseen classes, implying that conditional prompt tuning not only fits well to the base classes, but also generalizes to the unseen classes despite the class shift.

TABLE XI
PERFORMANCE ON BASE CLASSES AND NEW CLASSES.

	Cora	Art	Industrial	M.I.
		Performance or	base classes	
G2P2+d G2P2 G2P2*	28.81±3.35 52.50±1.38 48.60±1.68	$\begin{array}{ c c c c c c }\hline 40.04 \pm 2.35\\ \underline{43.47} \pm 2.59\\ \hline \textbf{44.29} \pm 2.30\\ \hline \end{array}$	47.24±2.71 52.84 ±1.72 <u>52.44</u> ±2.48	41.12±3.63 49.89±4.76 49.29±4.25
	F	Performance on	unseen classes	
G2P2+d G2P2 G2P2*	$\begin{array}{ c c c c c c }\hline & 22.51 \pm 1.41 \\ & \underline{24.83} \pm 2.71 \\ \hline & \textbf{25.70} \pm 1.25\end{array}$	$\begin{array}{ c c }\hline 38.01 \pm 0.74\\\hline 31.97 \pm 4.69\\\hline 41.43 \pm 1.28\\\hline \end{array}$	51.80±1.66 39.71±1.66 50.77±1.74	39.64±3.88 37.49±3.95 45.95 ±1.92

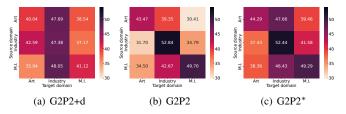


Fig. 6. Generalizability of G2P2 variants across domains.

Generalizing across domains. In the preceding part, we have investigated the ability to generalize to unseen classes within the same domain (dataset). In the following, we aim to examine the generalization to unseen classes across different domains. The ability to generalize to out-of-distribution data is a crucial feature in real-world scenarios. It is intriguing to determine whether the handcrafted or learned prompts can withstand shifts across different domains. Hence, we conduct experiments on the three Amazon datasets, each representing a different domain. Specifically, we select or tune prompts using the labeled data of the base classes from a source domain, and apply the prompts for inference on the test set of the base classes from each target domain. As illustrated in Fig. 6, among the three variants, the discrete prompts in G2P2+d have exhibited the poorest fit on the source domains but demonstrated reasonable generalizability across other domains. In contrast, the learnable static prompts in G2P2 fit optimally on the source domains but showed the poorest generalizability across other domains. Finally, the conditional prompts in G2P2* has performed well on both the source and target domains, showing their ability in not only fitting to the source domain but also generalizing across domains.

Comparing G2P2* with a bigger G2P2. Given that G2P2* incorporates a larger number of parameters than G2P2, specifically through the addition of the Meta-Net, it is important to investigate if the observed improvements by G2P2* are merely a consequence of parameter size. Hence, we use more context tokens in G2P2 so that its number of parameters becomes comparable to that of G2P2*. Specifically, the number of context tokens (M) is increased to 16 from 4 in G2P2, and we report the resulting performance in Tab. XII. The results indicate that merely increasing the parameter size does not lead to performance improvement. On the contrary, compared to M=4, M=16 gives worse performance on both base and unseen classes possibly due to overfitting in low-resource

TABLE XII
G2P2* VS. A BIGGER G2P2 ON ART.

	Param. size	Base classes	Unseen classes
G2P2 $(M = 4)$ G2P2 $(M = 16)$ G2P2* $(M = 4)$	2,048 8,192 7,688	$\begin{array}{ c c }\hline 43.47 \pm 2.59\\\hline 40.74 \pm 3.31\\\hline 44.29 \pm 2.30\\\hline \end{array}$	$\begin{array}{ c c }\hline 31.97 \pm 4.69\\\hline 28.67 \pm 2.70\\\hline 41.43 \pm 1.28\\\hline\end{array}$

settings. Thus, conditional prompt tuning is a crucial design responsible for the improvements.

VI. CONCLUSION

In this paper, we studied the problem of low-resource text classification. Given that many text documents are related through an underlying network, we proposed a novel model called Graph-Grounded Pre-training and Prompting (G2P2). It consists of three graph interaction-based contrastive strategies in pre-training, and a prompting mechanism for the jointly pre-trained graph-text model in downstream classification. We further extended our model to G2P2* in order to deal with wider unseen classes. Finally, we conducted extensive experiments and showed the advantages of G2P2 and G2P2* in low-resource text classification.

A limitation of this work lies in the efficiency of the proposed G2P2*, as it incurs substantial time and memory overhead. This can be attributed to our instance-wise conditional design, which necessitates an individual forward pass of instance-specific prompts through the text encoder for each node. In contrast, G2P2 only requires a single forward pass for an entire minibatch, making it more efficient. Therefore, a potential avenue for future research is to explore the development of conditional prompt learning with a more efficient implementation. Another limitation of this work is the need of a graph to complement the texts. Although graphs are ubiquitous in information retrieval applications, in the case that an organic graph is unavailable, a potential solution is to construct synthetic graphs based on word co-occurrences or other relations, *e.g.*, linking up news articles in close time periods and locations.

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