A Unified Continuous Learning Framework for Multi-modal Knowledge Discovery and Pre-training

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Abstract

Multi-modal pre-training and knowledge discovery are two important research topics in multi-modal machine learning. Nevertheless, none of existing works make attempts to link knowledge discovery with knowledge guided multi-modal pre-training. In this paper, we propose to unify them into a continuous learning framework for mutual improvement. Taking the open-domain uni-modal datasets of images and texts as input, we maintain a knowledge graph as the foundation to support these two tasks. For knowledge discovery, a pre-trained model is used to identify cross-modal links on the graph. For model pre-training, the knowledge graph is used as the external knowledge to guide the model updating. These two steps are iteratively performed in our framework for continuous learning. The experimental results on MS-COCO and Flickr30K with respect to both knowledge discovery and the pre-trained model validate the effectiveness of our framework.

1 Introduction

Recent years have witnessed extensive research efforts to align the semantics across vision and language for various tasks, e.g., image-text retrieval [1][2][3][4], visual question answering [5][6], and phrase grounding [7][8]. In order to break boundaries between tasks, pre-training methods are developed to learn the cross-modal representations based on large-scale training corpora consisting of image-text pairs [9][10][11][12][13][14][15][16][17][18][19] and the learned model can be adapted to downstream tasks through fine-tuning.

Owing to the impressive power of the pre-trained model, existing research explores to identify multi-modal knowledge from the unstructured data of images and sentences. VisualSem [20] adopts CLIP [21] to identify semantic concepts from images, and MKGformer [22] unifies transformer [23] based encoders in different modalities with a hybrid manner for multi-modal knowledge graph completion. In the other direction, researchers also explore to inject external knowledge into the process of multi-modal pre-training. Taking scene graph as external knowledge, ERNIE-ViL [24] devise the graph masking strategy to utilize intra-modality knowledge in the language side, and ROSITA [25] extend the strategy to both modalities for fine-grained semantic alignment. These models are competitive and achieve impressive performance in downstream tasks.

Nevertheless, none of existing works make attempts to link knowledge discovery with knowledge guided multi-modal pre-training. We argue that there are several advantages to link them together. First, it naturally forms a continuous multi-modal learning paradigm which makes full use of training data without any annotation efforts in obtaining the explicitly labeled knowledge graphs (e.g., scene graph). Second, the knowledge graph could help to guide the pre-training process in return, which enables better performances for downstream tasks.
To this end, we propose to integrate knowledge discovery and knowledge guided multi-modal pre-training into a unified continuous learning framework in this paper. The overall architecture is presented in Figure 1. We take open-domain unstructured data of images and texts as input to align the two modalities. A multi-modal knowledge graph is maintained as the foundation of our framework to support knowledge discovery and model pre-training. For knowledge discovery, a pre-trained model is used to extract knowledge units from the uni-modal datasets and update the knowledge graph by linking multi-modal semantic units. For model pre-training, the knowledge graph is used as the external knowledge to guide the updating of the multi-modal model.

In practice, the multi-modal graph includes three kinds of nodes to cover multiple levels of semantic units, namely, image, sentence and concept (objects in the vision side and phrases in the language side). Knowledge discovery is then treated as a link prediction task on the knowledge graph taking pre-training model as a probe. Model training is then guided by the links predicted in the knowledge discovery process. These two steps are performed iteratively for continuous learning. In the optimization, we design confidence score aware soft labels and add regularization to mitigate the problem of error propagation.

For knowledge discovery, we evaluate the quality of edges identified in the multi-modal knowledge graph. For the pre-trained model, we evaluate its performance on one typical downstream task, i.e., image-text retrieval. Experiments on MS-COCO [1] and Flickr30K [8] demonstrate the effectiveness of our proposed framework. We also configure the noisy uni-modal datasets to validate the robustness of our model and results show that the framework can perform reliable model training even in the noisy environment.

2 Related Work

Vision-Language Representation Learning. Following BERT [26], UNITER [27], Unicoder [14], ERNIE-ViL [24] and VinVL [18] pre-train the vision-language transformer model on the large-scale annotated image-sentence pairs to learn the knowledge of the inter-modality links. In language pre-training, explicitly incorporating external knowledge to enhance model pre-training is investigated by ERNIE [28] and widely explored in recent years [30, 31, 32]. The knowledge facilitates model pre-training by an improved structural masked language model to enhance the modeling in structure, such as syntactic and semantic. In the vision-language pre-training, ERNIE-ViL [24] and ROSITA [25] integrate the knowledge of concepts from image and sentence to enhance the semantic alignments. In our work, we introduce a multi-modal knowledge graph in the dataset where the concepts, namely, phrases and objects, are unified.

Knowledge Discovery via Link Prediction. The construction of knowledge graph aims to predict the missing relation or entity in the triple [33, 34, 35, 36, 37]. In multi-modal knowledge graph, [34] constructs datasets to predict the multi-relational links between entities associated with numerical and visual data. VisualSem [20] adopts CLIP [21] to identify semantic concepts from images. To test the model’s generalization ability, [37] presents an open-world knowledge graph completion model to predict the links among entities unseen in training set. These works concentrate on knowledge discovery with the fixed multi-modal model. Different from these works, we perform knowledge discovery in a unified framework which unifies knowledge discovery and multi-modal pre-training.

Figure 1: The unified framework which unifies knowledge discovery and multi-modal pre-training.
discover and multi-modal model training in an iterative way, thus the knowledge graph is obtained with the progressively improved multi-modal model.

**Pseudo Labeling** Given the class labels, pseudo-labeling [38, 39] aims to pick a pseudo one for unlabeled samples with a model trained on labeled data. [38] produces pseudo-labels from the prediction of a trained model. [40] assigns labels for unlabeled samples through the propagation on the graphs. [39] incorporates confidence scores for unlabeled samples on the density of a local neighborhood. [41] considers the uncertainty of the confidence score for better network calibration. In the classification based pseudo labeling, the label is determined by the threshold. The same method in link assignment leads to popular nodes dominate the graph which degrades the graph quality and hinders the training of nodes with less edges. Thus, we estimate the popularity and devise the label-aware threshold for link assignment.

### 3 Continuous Learning Framework

The workflow of our continuous learning framework is presented in Algorithm 1. Given two uni-modal datasets (images and texts) and an initialized version of multi-modal pre-training model, we aim to deliver a multi-modal knowledge graph and an updated version of the pre-training model. In each iteration $t$, the knowledge graph and the pre-training model can be updated through knowledge discovery and model training.

**3.1 Task Preliminary**

**Uni-modal Datasets.** Given two Uni-modal datasets of images $I$ and texts $T$, we construct a knowledge graph and train the multi-modal pre-training model.

**Multi-modal Knowledge Graph.** We maintain a graph $\mathcal{G}$ to store the multi-modal knowledge. It has four kinds of nodes: image $I \in \mathcal{I}$ and sentence $T \in \mathcal{T}$ in global level, object $O$ and phrase $P$ in local level. It has two kinds of edges: intra-modality ones $(L(O,I), L(P,T))$ and inter-modality ones $(L(I,T), L(O,P))$. For intra-modality edges, we have link $L(O,I) = 1$ if $O \in I$ and $L(P,T) = 1$ if $P \in T$.

**Knowledge Discovery.** We identify cross-modality edges, i.e., $\{L(I,T), L(O,P)\}$, in the multi-modal knowledge graph for knowledge discovery. This starts with a multi-modality pre-training model $F_\theta$, and it assigns confidence scores in $[0, 1]$ to cross-modality edges as Eq. (1).

$$F_\theta(I, T) \to [0, 1], \quad F_\theta(O, P) \to [0, 1], \quad \text{where } O \in I, \quad P \in T$$

**Multi-modal Pre-training.** We sample cross-modality edges $(\{\hat{L}(I,T), \hat{L}(O,P)\})$ from the multi-modal knowledge graph as supervisions for continuous multi-modal pre-training.

### 3.2 Knowledge Discovery as Link Prediction on Multi-modal Graph

We treat knowledge discovery as the task of link prediction on the multi-modal graph on two semantic levels, namely, global level (image and sentence) and local level (object and phrase).

**3.2.1 Global Level Link Prediction**

Given a node pair that contains an image $I$ and a sentence $T$, the pre-trained model is employed to compute a confidence score to determine the existence of the edge. This is regarded as a classification problem and a threshold $\lambda$ is introduced to make the decision [38] 39. The calculation is shown in Eq. (2).

$$\hat{L}(I,T) = 1[F_\theta^{-1}(I, T) \geq \lambda] \quad (2)$$

**Label-aware Link Assignment (LA).** After link prediction on the graph, images are labeled with connected sentences, or vice versa. Following this interpretation, we can regard $I$ as input and $T$ as label in Eq. (2). Some nodes (image or sentences) in the graph might be more popular than others. Nodes with less edges suffer from the problem of under-training. And links connected to these kinds of nodes tend to obtain lower confidence scores. To mitigate this problem, we propose to set the threshold dynamically for a link considering the popularity of nodes (also known as labels) it connects.
to. First, we estimate the confidence score $\mathbb{P}(L = 1|I)$ of the label to measure its popularity $E(I)$ as Eq. (3). We assume sentence $T$ is sampled from an empirical (uniform) distribution and $\mathbb{P}(T|I)$ is thus constant.

$$\mathbb{P}(L = 1|I) = \sum_T \mathbb{P}(L = 1|T, I) \mathbb{P}(T|I) \approx \frac{1}{|\{T_k\}|} \sum_{T_k} \mathbb{P}(L = 1|T_k, I) = E(I) \quad (3)$$

In addition, we add the power hyperparameter $\mu$ to compute the corresponding label-aware threshold $\lambda(I)$. So is for sentence $T$.

$$\lambda(I) = [E(I)]^\mu \quad (4)$$

**Bi-label Link Assignment (BL).** For a cross-modality edge, both nodes it connects obtain popularity scores. Thus, we propose to consider thresholds of both nodes for link prediction and classify links into two categories, namely strong and weak ones. If the confidence score of a link is higher than both thresholds, it is treated as a strong one. If the score is only higher than one threshold, it is a weak one. We denote $\hat{L}_{(I,T)} = 0.5$ for weak links. Overall, the links between image $I$ and sentence $T$ can be summarized as Eq. (5).

$$\hat{L}_{(I,T)} = \frac{1}{2} \times (\mathbb{1}[F_{\theta}^{t-1}(I, T) \geq \lambda(I)] + \mathbb{1}[F_{\theta}^{t-1}(I, T) \geq \lambda(T)]) \quad (5)$$
3.2.2 Local Level Link Prediction

For the local level, we link concepts in different modalities. For computation efficiency, we only consider links between objects and phrases whose global nodes (image and sentence) are connected in the graph. On the language side, we utilize spacy\footnote{https://spacy.io/} for noun phrases identification and filter out those with low frequency to form a phrase set. On the vision side, an object detector is used to locate objects\cite{42}. Following\cite{43}, the representation of phrase is computed through mean-pooling of its tokens, then we measure the cosine similarity between the phrase and all objects in image $I$. Softmax is utilized to normalize the similarity scores. At last, the object whose similarity score is larger than $\lambda_C$ would be linked to the phrase.

$$L^t_{(O,P)} = \mathbb{1}[F^t_{\theta}^-(I,T) \neq 0] \mathbb{1}[F^t_{\theta}^- (O,P) \geq \lambda_C]$$ (6)

3.3 Multi-modal Pre-training

Based on the constructed multi-modal knowledge graph, we sample cross-modality links for model training. Links in the graph are identified automatically without human monitoring, therefore it is likely to contain noisy supervision. In order to mitigate the problem of error propagation, we propose a confidence score aware mechanism for model pre-training. We use image-text matching as the pre-training task. Note that, our framework is compatible to include other pre-training tasks.

3.3.1 Graph Structure Enhanced Representation Learning

For an input image or sentence, we learn their representations taking the graph structure into consideration. For each node (image or sentence), two-hop neighbors are considered. Take image node as an example, the directly linked sentences and phrase nodes connected to these sentences are included. Therefore, we integrate multiple levels of semantic information into the learning process. In practice, the linked sentences $N_I = \{T|\hat{L}_t(I,T) = 1\}$ and corresponding phrases $P_I = \{P|P \in T, O \in I, \hat{L}_t(I,T) = 1, \hat{L}_t(I,O,P) = 1\}$ are concatenated to the original image to form an input sequence. The phrases share the token embedding with the sentence, and we add a new segment embedding vector to denote that it shares the semantics with the image instead of the sentence.

3.3.2 Confidence Score Aware Training

Instead of directly using hard labels as supervision we use confidence scores of links to construct soft labels for training. Losses are computed in both global (image-text) and local (phrase-object) levels.

**Global Level Loss.** There are three types of cross-modality edges between nodes according to the confidence score, namely, strong one, weak one and none. We construct a triplet for loss computation. Take the image as an example. For each image $I$, we randomly select a linked sentence node $T^+ \in \{T|\hat{L}_t(I,T) = 1\}$ to compose a positive pair. If there is no $T \in T$ satisfies the requirement, the sentence is sampled from the weak linked sentences $T^- \in \{T|\hat{L}_t(I,T) = 0.5\}$. The negative sentence $T^-$ is sampled from $\{T|\hat{L}_t(I,T) = 0\}$ that do not link to image $I$.

For these sampled links, we sharpen the confidence score by the exponential operation with hyperparameter $\gamma$. We observe that weak links are more likely to be mistakenly assigned than strong ones, another hyperparameter $\mu < 1$ is thus adopted on the group of weak ones. The label construction is shown in Eq. (7).

$$Y^t_{(I,T)} = \begin{cases} [F^t_{\theta}^-(I,T)]^\gamma, & \hat{L}_t(I,T) = 1 \\ \mu [F^t_{\theta}^-(I,T)]^\gamma, & \hat{L}_t(I,T) = 0.5 \\ 1 - [1 - F^t_{\theta}^-(I,T)]^\gamma, & \hat{L}_t(I,T) = 0 \end{cases}$$ (7)

The loss is shown in Eq. (8).

$$\mathcal{L}_{IT} = - \sum_{(I,T)} Y^t_{(I,T)} \log F_{\theta}(I,T)$$ (8)
Local Level Loss. For the linked pairs of objects and phrases, we regard the phrase $P$ as the anchor and collect all of $O \in I$ for the cross-entropy computation. In this level, we simply take $Y_{(O,P)}^t = L_{(O,P)}^t$ and optimize with the following Eq. (9):

$$L_C = - \sum_{(I,T)} Y_{(I,T)}^t \sum_{(O,P) \in I,F \in T} Y_{(O,P)}^t \log F_{\theta}(O,P)$$

Regularization to Reduce Uncertainty of Confidence. To ensure the reliability of the linking confidence scores, we further reduce the uncertainty during the training. MC Dropout [44] is employed for uncertainty estimation. For each input pair $(I,T)$, we perform forward computation twice of the model with different dropout and get the confidence scores $F_{\theta,1}(I,T)$ and $F_{\theta,2}(I,T)$ which can be regard as the two bernoulli distributions, then utilize the Jensen–Shannon divergence to minimize the distance which is shown in Eq. (10).

$$L_U = \frac{1}{2} KL (F_{\theta,1}(I,T)||F_{\theta,2}(I,T)) + \frac{1}{2} KL (F_{\theta,2}(I,T)||F_{\theta,1}(I,T))$$

The overall training loss of our model has three components as Eq. (11) with hyperparameters $\lambda_T$, $\lambda_C$, and $\lambda_U$.

$$L = \lambda_T L_T + \lambda_C L_C + \lambda_U L_U$$

4 Experiment

4.1 Experiment Setup

To validate the effectiveness of the proposed framework, we evaluate the performance on two tasks, knowledge discovery and cross-modal image-text retrieval under transductive setting. For knowledge discovery, we evaluate the performance of link prediction for both global level (image and sentence) and local level (object and phrase).

Dataset. The evaluation is performed on two benchmark datasets, MS-COCO [1] and Flickr30K [2]. In test split, MS-COCO and Flickr30K contain 5,000 and 1,000 images respectively, and each image is annotated with 5 text descriptions. In addition to text descriptions, Flickr30K also provides bounding box annotation for each phrase in the description, which enables local level link prediction. In total, there are 16,576 pairs of phrase and object.

Evaluation Metrics. For knowledge discovery, we follow [45] and use recall (R), precision (P) and F1 (F) as evaluation metrics for global level link prediction; while for local level link prediction, since it is equivalent to phrase grounding task, we follow [46] and use the accuracy as the evaluation metric. The accuracy is defined as the fraction of query phrases whose predicted bounding box overlaps ground-truth box with IoU larger than 0.5. For image-text retrieval, we report recall at $K$ (R@K) following the metrics in [47].

Implementation. We employ VinVL(base) [18] as our backbone. In our continuous learning framework, we need to initialize the multi-modal graph for an iterative optimization. As VinVL [18] (base) are not pre-trained with image-text matching task, CLIP is used to produce the initial linking confidence score between image and text for graph initialization. The hyperparameters are selected according to the results on randomly sampled 100 image-sentence pairs in validation set.

In the experiments, the dropout rate is 0.1. We set $\lambda_T, \lambda_C, \lambda_U = 1.0, 0.05, 0.5$ in Eq. (11), $\mu, \gamma = 0.6, 0.25$ in Eq. (7). The batch size is set as 32. Adam [48] with $\beta_1 = 0.9, \beta_2 = 0.999$ is used as the optimizer. We use the linear-decay learning rate scheduler with 10% warmup, and train the model with 15 and 20 epochs ($t_{max}$) on MS-COCO and Flickr30K, respectively.

During knowledge discovery, for computing image (sentence) popularity, we sample the counterpart sentences (images) which earn top-$K$ tiers. In MS-COCO, we set $K = 7, 2$ and the power parameter $\mu = 0.98, 1.0$ in Eq. (4) for image and sentence, respectively. While in Flickr30K, we set $K = 10, 2$ and power parameter $\mu = 0.96, 1.0$. For ablation study (§4.3) and other experiments (§4.4), we set the hyperparameters of $K$ and $\mu$ as the same with that in popularity computation for equal comparison.

For computation efficiency, during the knowledge discovery, instead of computing the linking confidence score for each pair across the unimodal datasets, which needs $\#T \times \#I$ times of
calculation, we firstly perform cross-modal retrieval with CLIP and select the top 40 candidate sentences (images) for each image (sentence), then the knowledge discovery of each image or sentence is limited in the corresponding 40 pairs. The number of calculation is reduced to \((\#T + \#I) \times 40\).

4.2 Performance Comparison

**Compared Baselines.** We compare the proposed framework with several vision language pre-trained models, including CLIP(ViT-B/32) [21] and VinVL(base) [18]. For knowledge discovery, in addition to CLIP and VinVL, we also compare with two weakly supervised phase grounding models, i.e., CLPG [49] and CKD [46] on Flickr30K in terms of local level link prediction. For Image-text retrieval, since our framework does not require any paired image-text data for training, for a fair comparison, the CLIP is evaluated under zero-shot setting, and VinVL is trained with the links obtained from CLIP.

**Results and Analysis.** Table 1 summarizes the performance comparison results. For knowledge discovery, our method achieves remarkable improvement compared with CLIP and VinVL for both global level and local level link prediction, showing the effectiveness of our method in knowledge discovery. It is worthwhile to mention that our method also outperforms weakly-supervised phase grounding methods CLPG and CKD for local level link prediction without any supervision. For image-text retrieval, similar observations can be founded. Our method outperforms both CLIP and VinVL, attaining the best performances in terms of image-text retrieval. The superior performances attained on both knowledge discovery and image-text retrieval demonstrate the effectiveness of the proposed iterative vision-text pre-training framework.

| Model   | Knowledge Discovery | Image-text Retrieval |
|---------|---------------------|----------------------|
|         | R | P | F | Acc | R@1 | R@5 | R@10 | R@1 | R@5 | R@10 |
| **Flickr30K** | | | | | | | | | | |
| CLPG [49] | - | - | - | 51.7 | - | - | - | - | - | - |
| CKD [46] | - | - | - | 53.1 | - | - | - | - | - | - |
| CLIP [21] | 42.6 | 54.1 | 47.7 | 59.2 | 94.7 | 98.3 | 58.6 | 83.4 | 89.9 |
| VinVL [18] | 64.1 | 80.3 | 71.3 | 99.1 | 99.7 | 75.1 | 93.5 | 96.1 | |
| **Ours** | 72.2 | 88.1 | 79.4 | 94.3 | 99.5 | 99.7 | 82.4 | 95.0 | 96.5 |

| **MS-COCO** | | | | | | | | | | |
| CLIP [21] | 11.7 | 28.7 | 16.7 | - | 50.2 | 75.0 | 83.6 | 30.4 | 56.0 | 66.9 |
| VinVL [18] | 29.1 | 70.7 | 41.2 | - | 65.8 | 86.3 | 90.8 | 50.2 | 75.2 | 81.7 |
| **Ours** | 33.6 | 79.5 | 47.2 | - | 71.5 | 87.2 | 91.7 | 54.0 | 76.5 | 82.3 |

4.3 Ablation Study

We further investigate the effectiveness of different modules in our framework, which includes knowledge discovery (KD), confidence score aware loss (CAL), graph structure enhanced representation learning (GL) and uncertainty reducing (UR) in multi-modal pre-training. Table 2 summarizes the ablation study results on Flickr30K using VinVL as the base model. From the results, we have the following observations. First, when adding each of the modules, the performances of both knowledge discovery and image-text retrieval have been improved, which suggests the effectiveness of these components. Second, it achieves the best performance when using all components, demonstrating these four modules are complementary to each other.

4.4 Discussion

**Continuous Learning Performance w.r.t Iteration Step.** In the test set of Flickr30K [8], we evaluate each iteration step of the framework to validate the effectiveness of the proposed continuous
Table 2: Ablation study in the test set of Flickr30K [2].

| Model  | R     | P     | F     | Acc   | R@1   | R@5   | R@10  | R@1   | R@5   | R@10  |
|--------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| VinVL  | 64.1  | 80.3  | 71.3  | 50.4  | 89.1  | 99.1  | 99.7  | 75.1  | 93.5  | 96.1  |
| +KD    | 68.0  | 83.9  | 75.1  | 55.1  | 91.1  | 99.1  | 99.7  | 77.8  | 94.2  | 96.2  |
| +CAL   | 70.8  | 85.7  | 77.5  | 56.8  | 92.8  | 99.1  | 99.7  | 80.1  | 94.6  | 96.3  |
| +GL    | 71.3  | 86.6  | 78.2  | 57.6  | 93.6  | 99.1  | 99.7  | 81.7  | 94.8  | 96.5  |
| +UR    | 72.2  | 88.1  | 79.4  | 58.7  | 94.3  | 99.5  | 99.7  | 82.4  | 95.0  | 96.5  |

learning strategy. The performance with respect to global level knowledge discovery and image-text retrieval is shown in Figure 2. From the table, we can see that as the iteration goes on, the overall performance in both tasks gets better in the early stage and is maintained in the later. This demonstrates that (1) the knowledge discovery and the multi-modal model can benefit each other for successive improvement; (2) despite the error in knowledge discovery is inevitable during the iteration, our framework with confidence score aware training can alleviate this issue hence preventing the failure of training.

Figure 2: Evaluation of each iteration step of the continuous learning framework in the test set of Flickr30K [8].
Effects of Different Link Assignment Strategies. As mentioned in §3.2.1, we have introduced different link assignment strategies in the process of knowledge discovery. These strategies include (1) the comparison one, absolute threshold based link assignment (AT) [38, 39] in Eq. (2), (2) label-aware link assignment (LA) and bi-label link assignment (BL) that can be successively added to VinVL. To investigate the effects of different strategies, we conduct experiments on Flickr30K datasets and the experimental results are reported in Table 3. To demonstrate that the proposed link assignment strategies are also effective in dealing with the imbalance problem in link prediction, we report the proportion of the links from popular nodes (%PP) that have more than 10 links. From the results, we find that: (1) The problem of imbalance is serious in VinVL and VinVL+AT. Through integrating LA and BL into VinVL, no nodes will have more than 10 links as the %PP is reduced to 0. (2) Compared to VinVL and AT, LA and BL successively improve the performance of link prediction as well as the image-text retrieval.

Table 3: Performances of different link assignment strategies on Flickr30K [2]. VinVL is used as the base model. Confidence score aware loss is adopted when using different link assignment strategies.

| Model | Knowledge Discovery | | Image-text Retrieval | |
|-------|---------------------|-----------------|---------------------|-----------------|
|       | %PP | R | P | F | R@1 | R@5 | R@10 | R@1 | R@5 | R@10 |
| VinVL | 30.7 | 64.1 | 80.3 | 71.3 | 89.1 | 99.1 | 99.7 | 75.1 | 93.5 | 96.1 |
| +AT   | 25.3 | 66.3 | 81.8 | 73.2 | 89.6 | 98.9 | 99.6 | 75.9 | 93.6 | 96.1 |
| +LA   | 3.8 | 74.5 | 73.9 | 74.2 | 91.3 | 99.1 | 99.7 | 78.3 | 94.0 | 96.2 |
| +BL   | 0.0 | 70.8 | 85.7 | 77.5 | 92.8 | 99.1 | 99.7 | 80.1 | 94.6 | 96.3 |

Performance of Inductive Learning. We then test the generalization ability of our pre-trained model under inductive learning where neither the pseudo graph nor the graph modeling is available. In our implementation, we randomly sample 1,000 images and the corresponding 5,000 sentences from the training set of Flickr30K to construct two unimodal datasets for training, and test the model in the Flickr30K. For comparison, we also train the CLIP [21] and VinVL [18] with the pairs under supervised setting. Supervised VinVL can be regarded as the upper bound. The results are summarized in Table 4.

From the results, our model outperforms VinVL in unsupervised setting and the supervised CLIP, and achieve comparable performance with supervised VinVL. The results basically suggest that our method generalizes well under inductive learning.

Table 4: Performance of multi-modal model in the Flickr30K testing set with inductive manner.

| Model | Image-to-Sentence | Sentence-to-Image | |
|-------|-------------------|-------------------|---|
|       | R@1 | R@5 | R@10 | R@1 | R@5 | R@10 |---|
| Supervised Learning | | | | | | | |
| CLIP   | 85.1 | 96.6 | 99.0 | 68.7 | 89.7 | 94.8 |
| VinVL  | 90.3 | 99.4 | 99.8 | 79.4 | 94.6 | 96.5 |
| Unsupervised Learning | | | | | | | |
| CLIP   | 79.2 | 94.7 | 98.3 | 58.6 | 83.4 | 89.9 |
| VinVL  | 84.9 | 98.4 | 99.5 | 70.2 | 92.0 | 95.3 |
| Ours   | 91.2 | 99.5 | 99.8 | 78.3 | 94.1 | 96.1 |

Noisy Environment. To test the noise-resistant learning capability of the multi-modality model, we setup the noisy environment where not each sample in the uni-modal dataset has a corresponding counterpart. The clean version of unimodal datasets is composed of 500 images which are randomly sampled from the test set of Flickr30K and their corresponding 2,500 sentences. Then, we add noises
through (1) randomly adding 2,500 sentences of MS-COCO to the sentence based unimodal dataset; (2) adding 500 images from validation set of Flickr30K to the image based unimodal dataset; (3) both (1) and (2). The noisy samples do not have ground-truth links. We test it on the whole test set of Flickr30K with 1,000 images and 5,000 sentences. We list the results in Table 5.

From the table, we find that: (1) Compare to adding noise to either image or sentence based unimodal dataset, adding noise to both fails to predict another 2% ground-truth links. (2) Despite the degradation in the quality of the pseudo graph, our noisy-resistant model training is comparable among different settings. This validates the learning efficiency of our framework in the noisy environment.

Table 5: Performance comparison in the noisy environment. Noise-i is corresponding to the i-th noise adding strategy in the section of Noisy Environment.

| Data    | Global | Image-to-Sentence | Sentence-to-Image |
|---------|--------|-------------------|-------------------|
|         | R   | P    | F    | R@1 | R@5 | R@10 | R@1 | R@5 | R@10 |
| Clean   | 76.8 | 89.9 | 82.8 | 91.5 | 99.3 | 99.6 | 77.8 | 94.5 | 96.2 |
| Noise-1 | 74.3 | 89.5 | 81.2 | 92.2 | 99.4 | 99.7 | 78.1 | 94.0 | 96.1 |
| Noise-2 | 74.3 | 86.7 | 79.2 | 92.5 | 99.4 | 99.6 | 77.9 | 94.3 | 96.3 |
| Noise-3 | 72.6 | 82.1 | 77.1 | 92.4 | 99.3 | 99.7 | 77.0 | 94.1 | 96.1 |

Random Uni-modalDatasets where No Ground-truth Link Exists. To demonstrate that our framework does not heavily rely on the selection of the unimodal datasets, we setup a random environment where none of image or sentence has ground-truth counterpart. In the environment, instead of selecting both of image and text based uni-modal datasets from Flickr30K testing set in §4.1, we keep the 1,000 images of Flickr30K testing set as the image based uni-modal dataset, and pick up 5,000 sentences from MS-COCO training set to compose the text based uni-modal dataset. In evaluation, considering that no ground-truth link exists in the random environment, we ignore the task of knowledge discovery and only report the performance of image-text retrieval in Flickr30K testing set. The first three comparison models are trained with the uni-modal datasets where both of the image and text based uni-modal datasets from the Flickr30K testing set. The result is listed in Table 6. From the table, we find that the missing of ground-truth counterpart degrades the model performance in image-text retrieval. Compare with VinVL(Random) and the counterpart model VinVL, Ours(Random) has less performance drop from its counterpart. The performance of Ours(Random) is better than CLIP and comparable with VinVL which are trained with the uni-modal datasets where the ground-truth link exists. This demonstrates that our framework is effective when training on random unimodal datasets.

Table 6: Performance comparison in the random environment where none of image or sentence has ground-truth counterpart. The first three comparison models are trained with the uni-modal datasets where the ground-truth link exists.

| Model     | Image-to-Sentence | Sentence-to-Image |
|-----------|-------------------|-------------------|
|           | R @1 | R@5 | R@10 | R@1 | R@5 | R@10 |
| CLIP [21] | 79.2 | 94.7 | 98.3 | 58.6 | 83.4 | 89.9 |
| VinVL     | 89.1 | 99.1 | 99.7 | 75.1 | 93.5 | 96.1 |
| Ours      | 92.2 | 99.4 | 99.7 | 78.1 | 94.0 | 96.1 |
| VinVL(Random) | 75.9 | 98.1 | 99.5 | 66.8 | 92.2 | 95.6 |
| Ours(Random) | 89.7 | 99.3 | 99.7 | 75.7 | 93.2 | 96.0 |

5 Conclusion

In this paper, we propose a unified continuous learning framework for multi-modal knowledge discovery and pre-training based on two uni-modal datasets. In the framework, knowledge discovery
is regarded as the problem of inter-modality link prediction on a multi-modal knowledge graph. Multi-modal pre-training is then performed with the guidance of the knowledge graph. In order to mitigate the error propagation problem in the iterative process, we propose label-aware link assignment strategy based on the popularity of nodes in the graph construction. For model pre-training, we take graph structure as the knowledge for guidance. In practice, two-hop neighbors are utilized for the node representation learning. The experiments on Flickr30K and MS-COCO validate the quality of the multi-modal graph and the performance of pre-training model. The further analysis in the noisy environment also demonstrates that our system can perform reliable model training.

There are three major future directions. Firstly, more pre-training tasks on the multi-modal graph can be introduced to our framework for better model pre-training. Secondly, it would be interesting to explore a more efficient way for better continuous learning with efforts on quality control of the multi-modal knowledge graph. Thirdly, we would like to explore the structure of multi-modal graph for better cross-modality knowledge representation.

References

[1] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In European conference on computer vision, pages 740–755. Springer, 2014.

[2] Peter Young, Alice Lai, et al. From image descriptions to visual denotations: New similarity metrics for semantic inference over event descriptions. T-ACL, 2014.

[3] Zhihao Fan, Zhongyu Wei, Zejun Li, Siyuan Wang, and Jianqing Fan. Negative sample is negative in its own way: Tailoring negative sentences for image-text retrieval. arXiv preprint arXiv:2111.03349, 2021.

[4] Zhihao Fan, Zhongyu Wei, Zejun Li, Siyuan Wang, Haijun Shan, Xuanjing Huang, and Jianqing Fan. Constructing phrase-level semantic labels to form multi-grained supervision for image-text retrieval. arXiv:2109.05523, 2021.

[5] Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C Lawrence Zitnick, and Devi Parikh. Vqa: Visual question answering. In Proceedings of the IEEE international conference on computer vision, pages 2425–2433, 2015.

[6] Yash Goyal, Tejas Khot, Douglas Summers-Stay, Dhruv Batra, and Devi Parikh. Making the v in vqa matter: Elevating the role of image understanding in visual question answering. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 6904–6913, 2017.

[7] Licheng Yu, Patrick Poirson, Shan Yang, Alexander C Berg, and Tamara L Berg. Modeling context in referring expressions. In European Conference on Computer Vision, pages 69–85. Springer, 2016.

[8] Bryan A Plummer, Liwei Wang, Chris M Cervantes, Juan C Caicedo, Julia Hockenmaier, and Svetlana Lazebnik. Flickr30k entities: Collecting region-to-phrase correspondences for richer image-to-sentence models. In Proceedings of the IEEE international conference on computer vision, pages 2641–2649, 2015.

[9] Jiasen Lu, Dhruv Batra, Devi Parikh, and Stefan Lee. Vilbert: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks. Advances in neural information processing systems, 32, 2019.

[10] Liunian Harold Li, Mark Yatskar, Da Yin, Cho-Jui Hsieh, and Kai-Wei Chang. Visualbert: A simple and performant baseline for vision and language. arXiv preprint arXiv:1908.05557, 2019.

[11] Weijie Su, Xizhou Zhu, Yue Cao, Bin Li, Lewei Lu, Furu Wei, and Jifeng Dai. Vi-bert: Pre-training of generic visual-linguistic representations. arXiv preprint arXiv:1908.08530, 2019.
[12] Xiujun Li, Xi Yin, Chunyuan Li, Xiaowei Hu, et al. Oscar: Object-semantics aligned pre-training for vision-language tasks. ECCV, 2020.

[13] Hao Tan and Mohit Bansal. Lxmert: Learning cross-modality encoder representations from transformers. arXiv:1908.07490, 2019.

[14] Gen Li, Nan Duan, Yuejian Fang, et al. Unicoder-vl: A universal encoder for vision and language by cross-modal pre-training. In AAAI, 2020.

[15] Luowei Zhou, Hamid Palangi, Lei Zhang, Houdong Hu, Jason Corso, and Jianfeng Gao. Unified vision-language pre-training for image captioning and vqa. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 13041–13049, 2020.

[16] Junnan Li, Ramprasaath Selvaraju, Akhilesh Gotmare, Shafiq Joty, Caiming Xiong, and Steven Chu Hong Hoi. Align before fuse: Vision and language representation learning with momentum distillation. Advances in Neural Information Processing Systems, 34, 2021.

[17] Wonjae Kim, Bokyung Son, and Ildoo Kim. Vilt: Vision-and-language transformer without convolution or region supervision. In International Conference on Machine Learning, pages 5583–5594. PMLR, 2021.

[18] Pengchuan Zhang, Xiujun Li, Xiaowei Hu, Jianwei Yang, Liujian Wang, Yejin Choi, and Jianfeng Gao. Vinvl: Revisiting visual representations in vision-language models. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5579–5588, 2021.

[19] Zejun Li, Zhihao Fan, Huaixiao Tou, and Zhongyu Wei. Mvp: Multi-stage vision-language pre-training via multi-level semantic alignment. arXiv preprint arXiv:2201.12596, 2022.

[20] Houda Alberts, Teresa Huang, Yash Deshpande, Yibo Liu, Kyunghyun Cho, Clara Vania, and Iacer Calixto. Visualsem: a high-quality knowledge graph for vision and language. arXiv preprint arXiv:2008.09150, 2020.

[21] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In International Conference on Machine Learning, pages 8748–8763. PMLR, 2021.

[22] Xiang Chen, Ningyu Zhang, Lei Li, Shumin Deng, Chuanqi Tan, Changliang Xu, Fei Huang, Luo Si, and Huajun Chen. Hybrid transformer with multi-level fusion for multimodal knowledge graph completion. arXiv preprint arXiv:2205.02357, 2022.

[23] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. Attention is all you need. In NeurIPS, 2017.

[24] Fei Yu, Jiji Tang, et al. Ernie-vil: Knowledge enhanced vision-language representations through scene graph. arXiv:2006.16934, 2020.

[25] Yuhao Cui, Zhou Yu, Chunqi Wang, Zhongzhou Zhao, Ji Zhang, Meng Wang, and Jun Yu. Rosita: Enhancing vision-and-language semantic alignments via cross-and intra-modal knowledge integration. In Proceedings of the 29th ACM International Conference on Multimedia, pages 797–806, 2021.

[26] Jacob Devlin, Ming-Wei Chang, et al. Bert: Pre-training of deep bidirectional transformers for language understanding. In NAACL, 2019.

[27] Yen-Chun Chen, Linjie Li, Licheng Yu, Ahmed El Kholy, Faisal Ahmed, Zhe Gan, Yu Cheng, and Jingjing Liu. Uniter: Universal image-text representation learning. In European conference on computer vision, pages 104–120. Springer, 2020.

[28] Yu Sun, Shuohuan Wang, Yukun Li, Shikun Feng, Xuyi Chen, Han Zhang, Xin Tian, Danxiang Zhu, Hao Tian, and Hua Wu. Ernie: Enhanced representation through knowledge integration. arXiv preprint arXiv:1904.09223, 2019.
[29] Zhengyan Zhang, Xu Han, Zhiyuan Liu, Xin Jiang, Maosong Sun, and Qun Liu. Ernie: Enhanced language representation with informative entities. arXiv preprint arXiv:1905.07129, 2019.

[30] Weijie Liu, Peng Zhou, Zhe Zhao, Zhiruo Wang, Qi Ju, Haotang Deng, and Ping Wang. K-bert: Enabling language representation with knowledge graph. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 2901–2908, 2020.

[31] Ruize Wang, Duyu Tang, Nan Duan, Zhongyu Wei, Xuanjing Huang, Guihong Cao, Daxin Jiang, Ming Zhou, et al. K-adapter: Infusing knowledge into pre-trained models with adapters. arXiv preprint arXiv:2002.01808, 2020.

[32] Xiaozhi Wang, Tianyu Gao, Zhaocheng Zhu, Zhengyan Zhang, Zhiyuan Liu, Juanzi Li, and Jian Tang. Kepler: A unified model for knowledge embedding and pre-trained language representation. Transactions of the Association for Computational Linguistics, 9:176–194, 2021.

[33] Daniel Oñoro-Rubio, Mathias Niepert, Alberto García-Durán, Roberto González, and Roberto J López-Sastre. Answering visual-relational queries in web-extracted knowledge graphs. arXiv preprint arXiv:1709.02314, 2017.

[34] Ye Liu, Hui Li, Alberto Garcia-Duran, Mathias Niepert, Daniel Onoro-Rubio, and David S Rosenblum. Mmkg: multi-modal knowledge graphs. In European Semantic Web Conference, pages 459–474. Springer, 2019.

[35] Pouya Pezeshkpour, Liyan Chen, and Sameer Singh. Embedding multimodal relational data for knowledge base completion. arXiv preprint arXiv:1809.01341, 2018.

[36] Haseeb Shah, Johannes Villmow, Adrian Ulges, Ulrich Schwanecke, and Faisal Shafait. An open-world extension to knowledge graph completion models. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, pages 3044–3051, 2019.

[37] Felix Hamann, Adrian Ulges, Dirk Krechel, and Ralph Bergmann. Open-world knowledge graph completion benchmarks for knowledge discovery. In International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems, pages 252–264. Springer, 2021.

[38] Dong-Hyun Lee et al. Pseudo-label: The simple and efficient semi-supervised learning method for deep neural networks. In Workshop on challenges in representation learning, ICML, volume 3, page 896, 2013.

[39] Weiwei Shi, Yihong Gong, Chris Ding, Zhiheng MaXiaoyu Tao, and Nanning Zheng. Transductive semi-supervised deep learning using min-max features. In Proceedings of the European Conference on Computer Vision (ECCV), pages 299–315, 2018.

[40] Ahmet Iscen, Giorgos Tolias, Yannis Avrithis, and Ondrej Chum. Label propagation for deep semi-supervised learning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5070–5079, 2019.

[41] Mamshad Nayeem Rizve, Kevin Duarte, Yogesh S Rawat, and Mubarak Shah. In defense of pseudo-labeling: An uncertainty-aware pseudo-label selection framework for semi-supervised learning. arXiv preprint arXiv:2101.06329, 2021.

[42] Ross Girshick. Fast r-cnn. In Proceedings of the IEEE international conference on computer vision, pages 1440–1448, 2015.

[43] Zi-Yi Dou and Nanyun Peng. Improving pre-trained vision-and-language embeddings for phrase grounding. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 6362–6371, 2021.

[44] Yarin Gal and Zoubin Ghahramani. Dropout as a bayesian approximation: Representing model uncertainty in deep learning. In International conference on machine learning, pages 1050–1059. PMLR, 2016.
[45] Yang Yang, Ryan N Lichtenwalter, and Nitesh V Chawla. Evaluating link prediction methods. 
Knowledge and Information Systems, 45(3):751–782, 2015.

[46] Liwei Wang, Jing Huang, Yin Li, Kun Xu, Zhengyuan Yang, and Dong Yu. Improving weakly supervised visual grounding by contrastive knowledge distillation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 14090–14100, 2021.

[47] Andrea Frome, Greg S Corrado, Jon Shlens, Samy Bengio, et al. Devise: A deep visual-semantic embedding model. In NeurIPS, 2013.

[48] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014.

[49] Tanmay Gupta, Arash Vahdat, Gal Chechik, Xiaodong Yang, Jan Kautz, and Derek Hoiem. Contrastive learning for weakly supervised phrase grounding. In European Conference on Computer Vision, pages 752–768. Springer, 2020.