[Arxiv 2020] COAD: Contrastive Pre-training with Adversarial Fine-tuning for Zero-shot Expert Linking [paper][code]

Node/Graph Tasks:
Node task that is to predict which authors/experts the external information (papers, news and personal homepages) refers to where the external information

Training Type:
Contrastive pre-training on dataset with known labels and adversarial fine-tuning on external dataset with unknown label information. The parameters are firstly optimized in pre-training stage and jointly optimized in fine-tuning stage.

Pretext task data, hybrid: structure - bipartite graph, feature - attributes of papers, labels - experts (authors of papers)
The contrastive pre-training procedure utilizes the **graph topology** to sample the positive and negative pairs and improve the ability to extract features of encoder through maximizing and minimizing the **similarity that based on node features** between positive and negative pairs, respectively. The adversarial fine-tuning procedure detach the private features from the shared features of the external information by setting another private encoders.

Initial short summary here

Predicting the expert from corresponding heterogeneous information has wide applications in real-world. Unfortunately, the linkages from information to experts are arduous to obtain and annotating labels beforehand is unrealistic. This paper proposes the contrastive pre-training with adversarial fine-tuning model to enable expert linking from the external sources. The contrastive learning is leveraged to pre-train the model that takes the attributes of the paper as the input and output its corresponding expert in the AMiner. The adversarial learning is leveraged to transferably learning the alignment of the external information to experts in the AMiner.

In pre-training module, 1) an encoder to capture the representation of experts from their published papers and 2) an interaction-based metric function to measure the similarity between the experts are jointly trained by gradient descent. The parameters of the encoder and the metric function $\theta_g, \theta_{\mathbf{f}}$ are optimized through minimizing the triplet loss $L^{\text{pre-train}}$ defined by sampling the anchor instance $\mathbb{I}_e$ from the expert e and calculating the similarity f of its positive and negative pairs $\mathbb{I}_e^+, \mathbb{I}_e^-$ as following:

$$L^{\text{pre-train}}(\theta_g, \theta_{\mathbf{f}}) = \sum_{(\mathbb{I}_e, \mathbb{I}_e^+, \mathbb{I}_e^-)} \max\{0, m + f(e, e^-) - f(e, e^+)\} \quad (1)$$

In adversarial fine-tuning module, an adversarial learning algorithm that fine-tunes g, f to adapt to the external data is designed. Two generators $g^{\text{shared}}, g^{\text{private}}$ are introduced where g^{shared} is to extract similar features as AMiner experts from the external experts, and g^{private} is to extract domain-specific features from the external experts. Meanwhile, we create a domain discriminator and task predictor, and by crippling ability of the domain discriminator to distinguish sources of the shared features and enhance the predictive ability of the predictor with the private features, parameters $\theta_g^{\text{shared}}, \theta_{\mathbf{f}}$ in g^{shared}, f are fine-tuned to be generalized to the external dataset. The above procedures are realized by optimizing the following loss functions, respectively.

$$L^{\text{diff}}(\theta_g^{\text{shared}}, \theta_g^{\text{private}}) = \sum_{i=1}^{N_{\text{ext}}} ||g^{\text{shared}}(\mathrm{s_i})^{\mathrm{T}} g^{\text{private}}(\mathrm{s_i})||_2 \tag{2}$$

$$L^{\text{adv}}(\theta_g^{\text{shared}}, \theta_{\mathbf{h}}) = \sum_{i=0}^{N_{\text{AMiner}}} \log(\mathrm{MLP}(g^{\text{shared}}(s_i))) + \sum_{i=0}^{N_{\text{ext}}} \log(1 - \mathrm{MLP}(g^{\text{shared}}(s_i))) \tag{3}$$

$$\mathcal{L}^{\text{ext}}(\theta_g^{\text{private}}, \theta_h) = -\sum_{i=0}^{N_{\text{ext}}} \log(1 - \mathrm{MLP}(g^{\text{private}}(\widetilde{s_i}))) \tag{4}$$

$$\mathcal{L}(\theta_g^{\text{shared}}, \theta_g^{\text{private}}, \theta_f, \theta_h) = \mathcal{L}^{\text{pre-train}} + \alpha\mathcal{L}^{\text{adv}} + \beta\mathcal{L}^{\text{diff}} + \gamma\mathcal{L}^{\text{ext}} \tag{5}$$

Bibtex:

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