

# Prior-Guided Transfer Learning for Enhancing Item Representation in E-commerce

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## Abstract

Item representation learning is crucial for search and recommendation tasks in e-commerce. In e-commerce, the instances (e.g., items, users) in different domains are always related. Such instance relationship across domains contains useful local information for transfer learning. However, existing transfer learning based approaches did not leverage this knowledge. In this paper, we report on our experience designing and deploying Prior-Guided Transfer Learning (PGTL) to bridge this gap. It utilizes the instance relationship across domains to extract prior knowledge for the target domain and leverages it to guide the fine-grained transfer learning for e-commerce item representation learning tasks. Rather than directly transferring knowledge from the source domain to the target domain, the prior knowledge can serve as a bridge to link both domains and enhance knowledge transfer, especially when the domain distribution discrepancy is large. Since its deployment on the Taiwanese portal of Taobao in Aug 2020, PGTL has significantly improved the item exposure rate and item click-through rate compared to previous approaches.

## Introduction

In the Internet era, e-commerce portals (e.g., Amazon, eBay, Taobao) often contain hundreds of millions of items. It is difficult for users to find their desired items. Search and recommendation tasks aim to address such information overload problems. During this process, item representation learning is an important step. A proper item representation learned from a user interaction history can reflect item relationships and further help recommend similar items according to the user's preference. Recently, deep representation learning has attracted significant interest in this field (Barkan and Koenigstein 2016; Sun et al. 2017; Zhao et al. 2018). To obtain an effective deep model, it usually requires a massive amount of labeled training data. However it is not easy to collect sufficient data during the boost strapping stage of an e-commerce portal when it is still small with sparse user behaviors. In this case, transfer learning can be useful.

Transfer learning mainly studies how to transfer useful knowledge from a task with rich data in one domain (i.e., the source domain) to help a task with insufficient data in

another domain (i.e., the target domain). It has achieved significant success in the fields of natural language processing (NLP) and computer vision (CV) (Liu, Qiu, and Huang 2017; Wang et al. 2018, 2020; Yi et al. 2020). Due to the domain distribution divergence, the core of transfer learning is to learn domain-invariant knowledge so that the shared knowledge can be safely transferred from the source domain to the target domain. A popular approach is to build a fully-shared network to align domain distribution (Mou et al. 2016; Yang, Salakhutdinov, and Cohen 2017) or explicitly minimize the domain distribution discrepancy during the optimization process (Long et al. 2015; Ganin and Lempitsky 2015). Some advanced approaches find the discriminative knowledge with domain task characteristic is also necessary. They use both shared and private networks together to extract different kinds of features (Liu, Qiu, and Huang 2017; Yu et al. 2018; Qiu et al. 2019). However these existing approaches have not been widely applied in industrial e-commerce platforms because it is hard to directly align the global data distribution of millions of items.

In this paper, we report on our experience designing and deploying a novel Prior-Guided Transfer Learning (PGTL) framework into the Alibaba e-commerce platform to address the aforementioned gap. It leverages the prior knowledge on relationships of instances in different domains (which is readily available in e-commerce applications) to guide fine-grained transfer learning for item representation learning. PGTL consists of three key parts:

1. It extracts prior knowledge according to cross domain instance relationships for target domain instances.
2. It learns domain-invariant features with the prior knowledge by adversarial training, as well as the discriminative features in the target domain. Specifically, we propose a domain perspective network based on the typical shared domain embeddings to extract domain specific embeddings for both domains, which can enhance discriminative feature extraction in the respective domains.
3. It enriches the target domain discriminative features with the transferred prior knowledge to enhance learning performance. We have designed a gate technique to control the information flow from prior knowledge to the target domain, which can effectively convey useful knowledge and avoid negative transfer.

PGTL has been deployed on the Taiwanese portal of Taobao in Aug 2020 to recommend potential items of interest for users. Overall, it has improved the item exposure rate and the item click-through rate by 52.9% and 23.26% respectively compared to the previous approach. To the best of our knowledge, PGTL is the first prior guided transfer learning approach deployed in a large-scale e-commerce system. It can be easily adapted to other tasks as long as prior knowledge is available.

## Application Description

Item representation learning is important in e-commerce. It supports a variety of functions such as recommendation systems and product search engines. Recently, deep representation learning techniques are starting to be applied in this field. For example, Barkan and Koenigstein (Barkan and Koenigstein 2016) proposed item2vec which embeds item IDs into a low-dimensional representation space. Liang et al. (Liang et al. 2016) decomposed the user-item interaction matrix and the item-item co-occurrence matrix with shared item latent factors to obtain item and user embeddings. Zhao et al. (Zhao et al. 2018) extended item2vec to propose a basic framework to learn different types of embeddings. These approaches aim to learn item representations in a single domain with sufficient data.

Transfer learning is a popular technique to improve the performance of learning tasks with insufficient data (Pan and Yang 2010; Long et al. 2014). It can be divided into two categories according to whether there are labeled data in the target domain: 1) unsupervised domain adaptation and 2) supervised domain adaptation. Unsupervised domain adaptation assumes that only unlabeled data are available in the target domain. The core idea is to find a shared feature space which can reduce the domain distribution divergence (Lee et al. 2007; Qiu et al. 2017; Wang and Mahadevan 2008; Jiang et al. 2019; Feng, Yu, and Duarte 2020). Pan et al. (Pan et al. 2009) and Long et al. (Long et al. 2015) proposed to minimize the Maximum Mean Discrepancies (MMD) to align the domain distributions. Other advanced domain adversarial approaches utilize generative adversarial networks (GANs) (Goodfellow et al. 2014) to extract the domain-invariant features for transfer learning (Ganin and Lempitsky 2015; Tzeng et al. 2017).

In supervised domain adaptation, fine-tuning is the widely used technique. However, some parameters may be driven far away from their initial values during fine-tuning, which loses the initial knowledge (Li, Grandvalet, and Davoine 2018). A more effective way is to find a domain-invariant representation space for joint learning involving source and target domain data (Mou et al. 2016; Yang, Salakhutdinov, and Cohen 2017). Further more, studies have shown that the domain discriminative representation which maintain the domain characteristics is also important for domain adaptation (Liu, Qiu, and Huang 2017; Yu et al. 2018; Qiu et al. 2019). Nevertheless, these transfer learning approaches are not well-suited for application in industrial e-commerce platforms, as they cannot evaluate the global distribution and minimize the domain distribution divergence involving millions of items efficiently.

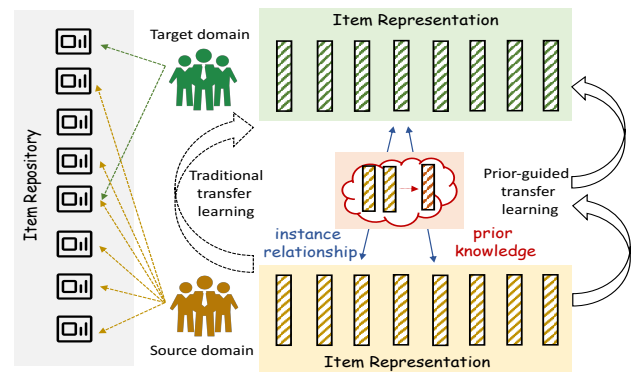


Figure 1: An illustration of the proposed PGTL approach. It leverages the prior knowledge, extracted with instance relationship across domains, to guide the fine-grained transfer learning-based item representation learning.

In e-commerce, even the same item or the same user can show different statistical characteristics due to preference diversity in various scenarios. This can result in domain distribution discrepancy. On the other hand, the cross domain instance relationship information is readily available. Based on such relationships, we can extract semantically similar source domain instances to generate the prior knowledge for target domain instances. The prior knowledge can serve as a semantic anchor to guide knowledge transfer in semantically similar items across domains (shown in Figure 1). The semantic anchor can also be a possible mechanism to scale up the domain distribution alignment in typical transfer learning to make it suitable for practical applications.

Intuitively, the prior knowledge derived from the source domain instances can provide complementary information to the target domain instances. Therefore, it can be leveraged to enrich the target domain knowledge to enhance task performance. However, not all prior knowledge is useful due to domain characteristics. For example, e-commerce data in simplified Chinese used in mainland China may not be useful prior knowledge for e-commerce applications in Taiwan which use traditional Chinese (although both domains are essentially using the same language).

PGTL belongs to the category of supervised domain adaptation. Its ability to leverage relationships between instances across domains to provide rich prior information to transfer learning distinguishes it from existing approaches. In addition, PGTL scales well to large datasets widely found in real-world e-commerce platforms. In the next section, we describe our AI Engine based on PGTL.

## Use of AI Technology

The goal of item representation learning is to find a latent representation space in which semantically similar items are close to each other and dissimilar ones are far apart. In this representation space, similar items can be easily retrieved given a query based on distance measures.

In this paper, we formalize this learning task as a binary classification problem  $\mathcal{L}$  that aims to predict whether a given

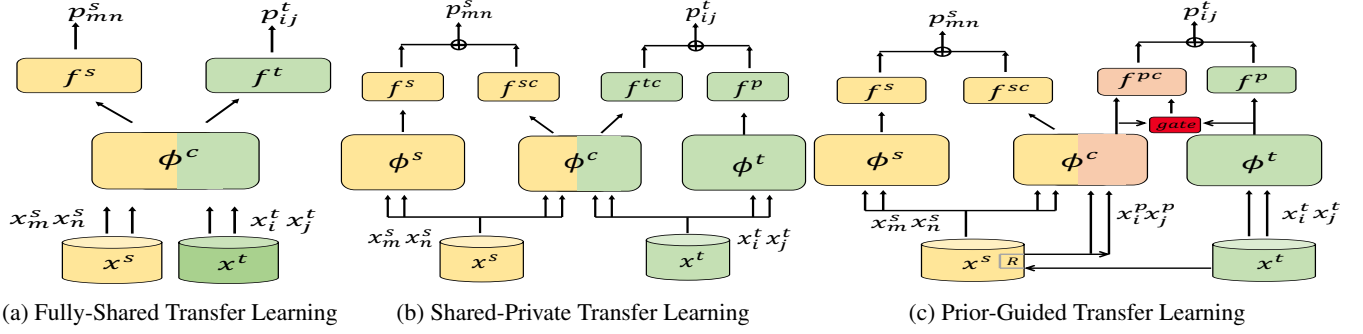


Figure 2: Comparing PGTL with traditional transfer learning approaches. PGTL first leverages the relationship  $R$  of cross domain instances to extract the prior knowledge, which in turn, is used to guide fine-grained transfer learning.

pair of items are similar or not. Given a set of items  $\{x_i\} \in \mathcal{X}$  and pairwise similarity label  $\{y_{ij}\} \in \mathcal{Y}$ ,  $y_{ij} \in \{0, 1\}$  denotes whether  $x_i, x_j \in \mathcal{X}$  are considered similar.

We attempt to learn the feature mapping  $\phi(\cdot)$  from the input space  $\mathcal{X}$  to the latent representation space  $\mathcal{Z}$  (i.e.,  $\phi: \mathcal{X} \mapsto \mathcal{Z}$ ), as well as the similarity prediction function  $f$  for pairwise instances (i.e.,  $f: \mathcal{Z} \times \mathcal{Z} \mapsto \mathcal{Y}$ ). Specifically, we construct the prediction function by using the cosine-distance to weigh the affinity. The probability for  $(x_i, x_j)$  to be regarded as similar is:

$$p_{ij} = \sigma(\cos(\phi(x_i), \phi(x_j)))$$

where  $\sigma$  is a Sigmoid function. Then, we can solve this problem by optimizing the following objective function:

$$\min_{\theta} \frac{1}{N} \sum_{i,j} \mathcal{L}_{task}(x_i, x_j, y_{ij}; \theta) + \beta\Omega(\theta) \quad (1)$$

where  $\mathcal{L}_{task}(x_i, x_j, y_{ij}) = -y_{ij} \log p_{ij} - (1 - y_{ij}) \log(1 - p_{ij})$  is the binary cross-entropy loss.  $\theta$  represents the parameters of feature mapping  $\phi$ .  $\Omega$  is a regularization term (e.g.,  $L_2$  regularization).  $\beta$  is a trade-off parameter.

## Background on Transfer Learning

In traditional transfer learning, we are given a source domain learning task  $\mathcal{L}_{task}^s$  with  $\mathcal{D}^s = \{(x_i^s, x_j^s, y_{ij}^s)\}_{i,j}^{N_s}$  of  $N_s$  labeled samples and a target domain learning task  $\mathcal{L}_{task}^t$  with  $\mathcal{D}^t = \{(x_i^t, x_j^t, y_{ij}^t)\}_{i,j}^{N_t}$  of  $N_t$  labeled samples (usually  $N_t < N_s$ ). The source domain data and target domain data follow different joint distributions  $P = (X^s, X^s, Y^s)$  and  $Q = (X^t, X^t, Y^t)$ , respectively (denoted as  $P \neq Q$ ). The goal of transfer learning is to improve the learning of the target feature mapping  $\phi^t(\cdot)$  and prediction function  $f^t$  using the shared knowledge in the source domain task.

Most existing transfer learning approaches aim to learn the domain-invariant features, which can be safely transferred from the source domain to the target domain. Usually, a common feature mapping  $\phi^c: \mathcal{X} \mapsto \mathcal{Z}^c$  is learnt to find the domain-invariant feature space  $\mathcal{Z}^c$  (as shown in Figure 2a). Furthermore, the data distribution discrepancy in the training objective is explicitly minimized to force the representation  $\phi^c(X^s)$  to follow a similar distribution as  $\phi^c(X^t)$ . Here, we

define the data distribution measure as  $Dist$ . The domain transfer objective can be expressed as:

$$\mathcal{L}_{trans}^{s,t}(\mathcal{D}^s, \mathcal{D}^t; \theta^c) = Dist_{\phi^c}(\mathcal{D}^s, \mathcal{D}^t). \quad (2)$$

Therefore, the entire training process can be optimized as:

$$\begin{aligned} \min_{\theta^c} & \frac{1}{N_s} \sum_{i,j} \mathcal{L}_{task}^s(x_i^s, x_j^s, y_{ij}^s; \theta^c) \\ & + \frac{1}{N_t} \sum_{i,j} \mathcal{L}_{task}^t(x_i^t, x_j^t, y_{ij}^t; \theta^c) \\ & + \lambda \mathcal{L}_{trans}^{s,t}(\mathcal{D}^s, \mathcal{D}^t; \theta^c) + \beta\Omega(\theta^c) \end{aligned} \quad (3)$$

where  $\mathcal{L}_{task}^s$  and  $\mathcal{L}_{task}^t$  are the task objectives defined in Eq. (1).  $Dist_{\phi^c}$  can be any distance measure (e.g., Maximum Mean Discrepancy (Gretton et al. 2012)).  $\lambda$  and  $\beta$  are trade-off parameters.

Apart from the shared domain-invariant features, recent works find that the domain specific features are also necessary as they contain domain characteristics and are more discriminative for domain classification tasks (Liu, Qiu, and Huang 2017; Yu et al. 2018; Qiu et al. 2019). Formally, we define another two domain specific feature mappings  $\phi^s: \mathcal{X}^s \mapsto \mathcal{Z}^s$  and  $\phi^t: \mathcal{X}^t \mapsto \mathcal{Z}^t$  to learn the domain discriminative features, respectively (Figure 2b). The final prediction combines both domain-invariant features and domain discriminative features:

$$\begin{aligned} p_{ij}^s &= \sigma(\cos(\phi^c(x_i^s), \phi^c(x_j^s)) + \cos(\phi^s(x_i^s), \phi^s(x_j^s))) \\ p_{ij}^t &= \sigma(\cos(\phi^c(x_i^t), \phi^c(x_j^t)) + \cos(\phi^t(x_i^t), \phi^t(x_j^t))) \end{aligned}$$

These frameworks aim to extract the shared domain-invariant knowledge across domains, and then directly combining it with target domain knowledge. In practical transfer learning problems in industrial e-commerce portals, minimizing the data distribution discrepancies involving millions of items is not easy, making it hard for existing transfer learning approaches to learn such a shared feature space. Especially when target domain data are insufficient, the model can easily pull dissimilar items together to minimize the whole distribution, resulting in semantic mismatches and negative transfer. In addition, as described before, not all transferred knowledge is useful for target domain tasks

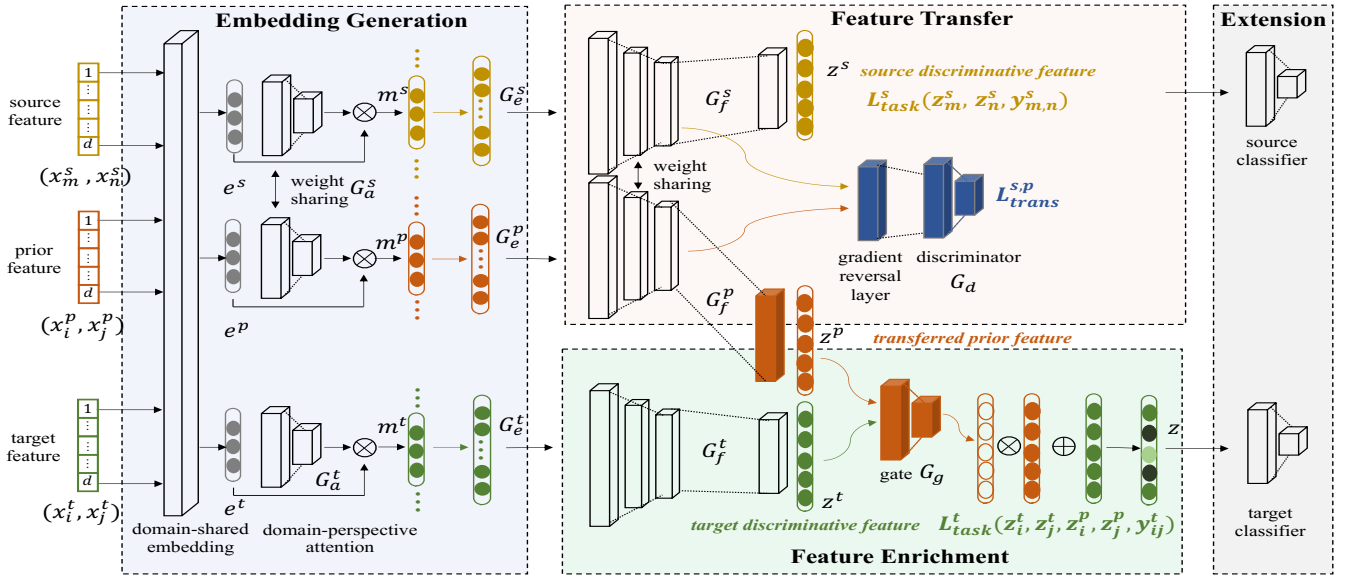


Figure 3: The PGTL framework with its three component parts: (1) Embedding Generation, an attention net to extract the domain specific embedding; (2) Feature Transfer, domain adversarial learning for transferring the source domain knowledge to prior knowledge; and (3) Feature Enrichment, incorporating the prior knowledge into target domain discriminative features.

due to domain characteristics. Selectively transferring useful knowledge can be an advantageous mechanism to avoid negative transfer.

### Prior-Guided Transfer Learning

Existing transfer learning methods mainly focus on the change of data distribution across domains from a global perspective without regard to the cross domain relationship among instances which can provide additional local information. For transfer learning scenarios in e-commerce, the source domain instances and target domain instances are often related. For example, the source domain items and target domain items are from the same product repository but show different statistical distributions due to different user preferences. PGTL leverages the data instance relationships across domains to extract prior knowledge for the target instances in order to enhance partial knowledge transfer.

Formally, for each target domain instance  $x_i^t$ , we define  $R_i = \{k\}_{r_{ik}=1}$  as the related source domain instance set.  $r_{ik} \in \{0, 1\}$  indicates whether the source domain instance  $x_k^s$  is related to target domain instance  $x_i^t$  (e.g., items  $x_k^s$  and  $x_i^t$  belonging to the same item category). According to the data instance relationship, we can extract the combined information of the related source domain instances as the prior feature for  $x_i^t$ , which is denoted as  $x_i^p$ . For example, if one target domain instance is related to multiple source domain instances, we can take the average features of related source domain instances as the prior knowledge (i.e.,  $x_i^p = \frac{1}{|R_i|} \sum_{k \in R_i} x_k^s$ ). When the source domain instance and target domain instance have a one-to-one relationship, the prior knowledge degenerates to the counterpart source domain features.

For a target domain task with a prior feature, it implicitly

constructs the prior domain task  $\mathcal{D}^p = \{(x_i^p, x_j^p, y_{ij}^p)\}_{i,j}^{N_t}$  of  $N_t$  labeled samples. The corresponding joint distribution is  $\tilde{Q}(X^p, X^p, Y^t)$ . Rather than directly reducing the discrepancy between  $P$  and  $Q$ , we first transfer knowledge from  $P$  to  $\tilde{Q}$ , and then enrich  $\tilde{Q}$  with  $\tilde{Q}$  for the target domain task (Figure 2c). Hence, the PGTL objective function is:

$$\begin{aligned} \min_{\theta^s, \theta^t, \theta^c, \theta^p} & \frac{1}{N_s} \sum_{i,j} \mathcal{L}_{task}^s(x_i^s, x_j^s, y_{ij}^s; \theta^s, \theta^c) \\ & + \frac{1}{N_t} \sum_{i,j} \mathcal{L}_{task}^{t,p}(x_i^t, x_j^t, x_i^p, x_j^p, y_{ij}^t; \theta^t, \theta^c, \theta^p) \\ & + \lambda \mathcal{L}_{trans}^{s,p}(\mathcal{D}^s, \mathcal{D}^p; \theta^s, \theta^c, \theta^p) + \beta \Omega(\theta^s, \theta^t, \theta^c, \theta^p) \end{aligned} \quad (4)$$

Compared to Eq. (3), PGTL is advantageous in two ways. Firstly, the knowledge transfer process is easier. Since the prior knowledge is derived from source domain instances, the data distribution discrepancy is naturally much smaller. Secondly, the target domain task can achieve better generalization performance with prior-enriched feature that is complementary to target feature.

The PGTL framework is shown in Figure 3. It contains three key parts: 1) the domain-perspective embedding extraction layers, 2) the domain-invariant feature transfer layers, and 3) the domain discriminative feature enrichment layers. The left portion of Figure 3 contains the embedding extraction layers. Besides the typical shared embedding layers, we further design two attention networks for the source domain and the target domain to extract the domain perspective embedding which is helpful for obtaining different discriminative features for the source task and the target task. In the upper-right portion of Figure 3, we apply the domain adversarial learning to derive the transferred domain-invariant

features for the source domain and the prior domain. Then, we enrich the target discriminative features with the transferred prior knowledge via a gate network to improve task performance (the bottom-right portion of Figure 3). The following sections describe each part in detail.

**Domain-perspective Embedding Extraction Layers** In previous studies, the target domain is always assumed to share the same embedding layers with the source domain. However, the domain agnostic embedding ignores the domain characteristics from the input layers, which is not useful to extract the discriminative features in subsequent layers for different tasks. Therefore, domain specific embedding is needed. A simple way to model domain specific embedding is to use individual embedding layers for each domain. However, it results in a huge number of parameters in the embedding layers which cannot be learned well with insufficient data in the target domain. To avoid parameter explosion, we design two individual small attention networks to provide domain perspective upon basic shared embedding in order to enhance the domain specific embedding.

Specifically, for an input  $x = [x^1, \dots, x^d] \in R^d$  with  $d$  types of features, PGTL first looks up the shared embedding matrix to obtain the feature embedding  $e^k$  for each feature  $x^k$ . Then,  $e^k$  is fed into the attention network to extract the domain perspective attention  $a^k$ . Next,  $a^k$  is applied upon  $e^k$  to obtain the domain perspective embedding  $m^k$ . Finally, all features are concatenated together to produce the final embedding  $G_e(x) = \text{Concat}(m^1, \dots, m^d)$ . Formally, we define the embedding generation network as:

$$\begin{aligned} e^k &= E(x^k; \theta_e) \\ a^k &= G_a(e^k; \theta_a) \\ m^k &= a^k \odot e^k \end{aligned}$$

where  $E$  is shared embedding matrix across domains.  $G_a$  is the domain specific attention network that can be instantiated by  $G_a^s$  for  $x^s$  and  $x^p$ , and instantiated by  $G_a^t$  for  $x^t$ .

**Domain-invariant Feature Transfer Layers** Typical transfer learning approaches transfer source domain knowledge to the target domain by learning domain-invariant features. However, in e-commerce portals with millions of items, it is hard for two different feature spaces to learn a shared feature space, especially when the domain distribution discrepancy is large. In PGTL, the source domain and the implicit prior domain are for different tasks, but share similar feature distributions. Thus, transferring source domain knowledge to the prior domain is much easier. Recently, domain adversarial networks have been successfully applied to transfer learning (Ganin and Lempitsky 2015; Tzeng et al. 2017; Guo et al. 2021). Here, we leverage such adversarial training to extract the domain-invariant features between the source domain and the prior domain.

The domain adversarial learning procedure is a two-player game, which contains two generators,  $G_f^s$  and  $G_f^p$ , and one discriminator  $G_d$ . During training,  $G_d$  learns to maximize the probability of assigning the correct label to samples from different domains, while  $G_f^s$  and  $G_f^p$  learn to maximize the probability of identifying the fake samples

generated by the discriminator. In such a two-player min-max game, the generator  $G_f^p$  and  $G_f^s$  will eventually achieve the same distribution.

For min-max optimization with back propagation, Ganin and Lempitsky proposed a special gradient reversal layer (GRL) as a ‘‘pseudo-function’’  $R(x)$  inserted between the feature generator and the domain classifier (Ganin and Lempitsky 2015). Its forward and back propagation behaviors are defined as:

$$\begin{aligned} R_\lambda(x) &= x \\ \frac{dR_\lambda}{dR_x} &= -\lambda \end{aligned} \quad (5)$$

The optimization objective for source and prior domain is:

$$\begin{aligned} \mathcal{L}_1 &= \frac{1}{N_s} \sum_{i,j} \mathcal{L}_{task}^s(G_y^s(G_f^s(G_e^s(x_i^s, x_j^s))), y_{ij}^s) + \frac{1}{N_s + N_t} \\ &\quad \sum_k^{N_s + N_t} \mathcal{L}_{trans}^{s,p}(G_d(R_\lambda(G_f^s(G_e^s(x_k^s))), G_f^p(G_e^p(x_k^p))), y_d) \end{aligned} \quad (6)$$

where  $\mathcal{L}_{task}^s$  is the source task objective defined in Eq. (1).  $\mathcal{L}_{trans}^{s,p}$  is cross-entropy loss,  $y_d$  is the domain label for discriminator and  $\lambda$  is the trade-off parameter.

**Domain Discriminative Feature Enrichment layers** After extracting the transferred prior knowledge, we use it to enrich the target discriminative features. Such prior knowledge can bring two benefits for the target domain task. On one hand, it contains rich transferred knowledge. On the other hand, the prior knowledge derived from the source domain feature space will provide complementary information to target discriminative features.

However, as described before, not all prior knowledge is useful for target domain tasks since different domains are with different characteristics. Therefore, we design a gate network to control the transfer flow of prior knowledge to the target domain. Let  $z^p$  and  $z^t$  denote the transferred prior feature and the discriminative target feature, respectively. Then, the gate is constructed as:

$$\begin{aligned} g &= G_g(z^p, z^t) \\ &= \sigma(\theta_g^T [z^p, z^t] + b_g) \end{aligned} \quad (7)$$

where  $\theta_g$  and  $b_g$  are weights and biases of the gate network, respectively.  $\sigma$  is a sigmoid function which produces the importance of prior knowledge. The final discriminative representation enriched by prior knowledge is:

$$g \odot z^p + z^t \quad (8)$$

and the target task objective is:

$$\mathcal{L}_2 = \frac{1}{N_t} \sum_{i,j} \mathcal{L}_{task}^{t,p}(G_y^t(g_i \odot z_i^p + z_i^t, g_j \odot z_j^p + z_j^t), y_{ij}^t). \quad (9)$$

The entire network is optimized as:

$$\min_{\theta} \mathcal{L}_1 + \mathcal{L}_2 + \beta\Omega(\theta). \quad (10)$$

	TaoBao		Ali-Express	
	CN(Src)	TW(Tgt)	RU(Src)	BR(Tgt)
# training	1.3B	0.2B	0.4B	0.1B
# test	1.3B	5.8M	0.3B	68M
# feature	36	36	42	42

Table 1: Statistics of the datasets

It is noteworthy that PGTL can be adapted to any transfer learning task once the prior knowledge is available. In addition, other advanced transfer learning techniques or gate techniques can be incorporated into PGTL if the need arises.

## Application Development and Deployment

To facilitate decision-making within Alibaba about whether to deploy PGTL online, our team has performed extensive offline experiments to compare its performance with state-of-the-art approaches.

## Experiment Settings

**Datasets** Due to the lack of public transfer learning datasets in e-commerce, we crawled the data from two large e-commerce websites, Taobao<sup>1</sup> and Ali-Express<sup>2</sup>, to construct two real-world industrial datasets.

Taobao is a large-scale e-commerce system, providing similar item catalogs for 13 regions. Mainland China is the biggest site generating billions of trading records daily, while smaller sites (e.g., Hong Kong) only generate millions of trading records daily. Even for the same item, different populations show different preferences, which causes data distribution divergence. We create the first dataset by collecting trading records in Mainland China as the source domain (referred to as CN), and the trading records in Taiwan as the target domain (referred to as TW). Ali-Express is another online recommendation system serving more than 200 countries around the world. The second dataset is created by collecting the trading records in Russia as the source domain (referred to as RU) and Brazil as the target domain (referred to as BR). In each dataset, we take two-weeks of trading records as the training data and one day of trading records as the test data. Table 1 summarizes the statistics of both datasets.

**Data preprocessing** Each record in the trading log is a user behavior log. It contains three parts: 1) user information (e.g., age, gender), 2) the exposure item information whether the user clicked the item or not which can be used as the click-through label in the click-through rate prediction task. For the item representation task, we manually extract the item similarity label. We take the current clicked item with historical clicked items in the user behavior logs as positive similar pairs. The sequentially clicked items tend to be similar. To construct the negative pairs, we take the current non-clicked item with historical clicked items in the user behavior logs as dissimilar pairs.

<sup>1</sup><https://taobao.com>

<sup>2</sup><https://www.aliexpress.com>

Since the source domain and the target domain share similar items, we can easily obtain the relationship of instances in the two domains. Specifically, we define cross domain items with the same item id as strongly related, and items belonging to the same item category as weakly related. When extracting the prior knowledge for target domain data, we first consider source domain items with strong relationships, and then with weak relationships if strong relationships are not available. The prior feature is generated by averaging all related source instance features.

In the following experiments, we select item profile features (e.g., price), item and seller statistic features, both short term and long term (e.g., CTR, CVR, GMV for 1 days, 7 days, 30 days) as item features. For each type of feature, we discretize dense feature to construct multiple hash buckets, and represent each hash bucket with an 8-dimension embedding. The final feature embedding is the concatenation of all hash bucket embeddings.

**Evaluation Metrics** We take AUC as the task performance metric. It is widely used in industrial e-commerce tasks (Qiu et al. 2019; Yu et al. 2018) and defined as follows:

$$AUC = \frac{1}{m^+m^-} \sum_{x^+ \in \mathcal{D}^+} \sum_{x^- \in \mathcal{D}^-} (I(f(x^+) > f(x^-)))$$

where  $\mathcal{D}^+$  is the collection of all positive examples and  $\mathcal{D}^-$  is the collection of all negative examples.  $f(\cdot)$  is the task prediction function and  $I(\cdot)$  is an indicator function.

Besides, we introduce the RelImpr metric to measure relative improvement of PGTL over existing approaches (Yan et al. 2014; Zhou et al. 2018). RelImpr measures the improvement ratio for two models with respect to a random guesser with an AUC of 0.5:

$$\text{RelImpr} = \left( \frac{\text{AUC}(\text{measure model}) - 0.5}{\text{AUC}(\text{base model}) - 0.5} - 1 \right) * 100\%.$$

**Comparison Baselines.** We compare PGTL with following existing approaches:

- Src-only: a basic model as defined in Eq. (1) trained from scratch on the source domain dataset.
- Tgt-only: a basic model as defined in Eq. (1) trained from scratch on the target domain dataset.
- Fine-tune: a basic transfer learning method that first trains the source model and then initializes the target model parameters with well trained source parameters.
- FShare: a fully-shared model as shown in Figure 2a which aims to learn only domain-invariant features (Yang, Salakhutdinov, and Cohen 2017).
- SShare: a state-of-the-art transfer learning model shown in Figure 2b which leverages shared and private model together to learn both domain-invariant features and domain discriminative features in other tasks (Yu et al. 2018). Since there are no specific transfer learning models for the item representation task, we construct the same framework for comparison.

Further, we design two variants of PGTL for ablation experiments to evaluate the effectiveness of each component part:



	Methods	AUC	RelaImpr
Base	Src-only	0.651	
	Tgt-only	0.593	
TL	Fine-tune	0.599	6.45%
	FShare	0.602	9.68%
	SShare	0.603	10.75%
	PGTL <sup>no specific embedding</sup>	0.606	13.97%
	PGTL <sup>no prior feature</sup>	0.605	12.90%
	PGTL	<b>0.611</b>	<b>19.40%</b>

Table 2: AUC of all approaches on the Taobao dataset.

	Methods	AUC	RelaImpr
Base	Src-only	0.692	
	Tgt-only	0.682	
TL	Fine-tune	0.682	0.0%
	FShare	0.686	2.19%
	SShare	0.679	-1.65%
	PGTL <sup>no specific embedding</sup>	0.683	0.55%
	PGTL <sup>no prior feature</sup>	0.688	3.29%
	PGTL	<b>0.692</b>	<b>5.49%</b>

Table 3: AUC of all approaches on Ali-Express dataset.

- PGTL<sup>no specific embedding</sup>: a PGTL variant which only uses shared embedding and does not consider the domain-specific embedding.
- PGTL<sup>no prior feature</sup>: a PGTL variant which does not consider the prior knowledge for the target domain. The prior feature is replaced with the target feature.

**Network Parameters** For all models, we use the Adam optimizer with learning rate starting from 0.0001. We set the activation function as tanh and the dropout probability  $p = 0.5$ . In the embedding layers, we set the basic bucket embedding dimension for each feature to 8 and the attention layers as [6,4,8]. In the feature generation layers, we set the hidden layers as [256,128]. In addition, we set the final item representation layer to 36 for Taobao and 42 for Ali-Express that corresponds to the number of input features.

## Results and Discussion

The performance of all comparison approaches on both datasets in terms of AUC is tabulated in Table 2 and Table 3, where the best performance achieved is in bold. It can be observed that PGTL achieves the best performance on the Taobao dataset, outperforming the single domain model Tgt-only by 19.40%. In contrast, the transfer learning baseline model that uses fine-tuning only improves over Tgt-only by 6.45%. Comparing to the more advanced transfer learning models FShare and SShare, PGTL has also achieved significant performance improvement by 9.72% and 8.65% respectively. Similar trends can be found for the Ali-Express dataset. The superiority of the PGTL is statistically significant. It is noteworthy that fine-tuning is not better than Tgt-

only on the Ali-Express dataset. This is because the parameters are driven far away from the initial values and little knowledge has been transferred. While the jointly trained models can effectively avoid this problem and achieve better performance.

The superior performance of PGTL over comparison approaches indicates that it is effective in transferring source domain knowledge to enrich the target domain. The previous models aim to reduce the domain distribution discrepancy to learn domain-invariant features. When the domain distribution discrepancy is large, the target domain does not benefit much, as shown in the results on the Ali-Express dataset. In this case, PGTL still achieves the best performance.

## Ablation Study

In this subsection, we further analyse the effect of domain-specific embedding and prior knowledge in PGTL and also visualize gate-control technique in case study.

**The effect of domain-specific embedding** We compare PGTL to PGTL<sup>no specific embedding</sup>, which drops the attention layers to study the effect of domain-specific embedding. Table 2 and Table 3 show that PGTL outperforms PGTL<sup>no specific embedding</sup> by 5.43% and 4.94% on the Taobao dataset and the Ali-Express dataset respectively. This suggests that domain specific embeddings are useful for enhancing discriminative feature learning in the following layers.

**The effect of prior knowledge** To study the effect of prior knowledge in PGTL, we use PGTL<sup>no prior feature</sup> for comparison which drops the actual prior feature and takes the target feature as the prior feature. This variant is similar to SShare, but with the domain specific embedding layers. It can be observed from Table 2 and Table 3 that PGTL outperforms PGTL<sup>no prior feature</sup> on both datasets. This shows that enriching the target domain features with prior knowledge is advantageous.

**The effect of gate-control** We conduct experiments with a one-dimensional gate and show the cases of different prior weights. We can easily find that everyday items always have higher prior weights. Particularly, for baby clothes, the prior weight can be as high as 0.98. On the other hand, the significant difference between Mainland China and Taiwan is the language used (i.e., simplified Chinese vs. traditional Chinese). We find items specially made for Taiwan (e.g., navigators in traditional Chinese) have very small prior weights. The results show that our gate network can selectively transfer useful knowledge to preserve the target domain characteristics when fusing with the transferred knowledge. These results helped Alibaba’s decision to deploy PGTL.

## Application Use and Payoff

The well trained item representation model produced by PGTL has been deployed in the Taiwanese portal of Taobao since Aug 2020 to support the “Guess what you like” service. This service is divided into two stages: 1) recalling a pool of candidate items, and 2) ranking these items. PGTL is part of the first stage, leveraging the relationships among



Figure 4: An example of gate weights for prior knowledge in the item representation learning task. The gate weights are larger for the first two cases, which are items popular in both Mainland China and Taiwan. The last two cases are items specially for Taiwan (e.g., navigators with traditional Chinese), for which the gate weights are smaller.

products from different domains to recall items which a given customers may be interested in.

When comparing the system performance as a result of deploying PGTL with the previous approach used by the Taiwanese portal of Taobao (which was a single domain item representation model), we use the relative improvement of item exposure ratio and item click-through rate as evaluation metrics. Overall, PGTL outperforms the previous approach by 52.9% in term of item exposure rate and 23.26% for item click-through rate. Such improvements show that the PGTL item representation model can find interested items for users more accurately, which in turn, can achieve significant positive business impact.

### Maintenance

The objectives of the PGTL AI Engine need to be set manually. Thus, we have conducted regular reviews of the system performance to make necessary adjustments. Other than this, no major maintenance task on the PGTL AI Engine was needed since its deployment in Aug 2020.

### Lessons Learned During Deployment

It is worth mentioning that even PGTL can guide the fine-grained transfer learning process and selectively transfer shared knowledge, there are still situations that the AI Engine could not handle. Here is an important lesson has been learned from our deployment experience which we feel is worth sharing.

Knowledge transfer in heterogeneous feature spaces is challenging, especially in industrial applications. One possible solution is to leverage partial shared features to learn domain-invariant knowledge, while leveraging specific features together with the shared features to learn domain discriminative knowledge (Guo et al. 2021). We are in the process of exploring adapting PGTL in such settings in order to improve its performance. During the current deployment effort, feature engineering still has to be performed as different applications always have features that are specific to each of them.

### Conclusions

In this paper, we reported on our experience designing and deploying a novel prior-guided transfer learning framework - PGTL, which effectively leverages the prior knowledge to guide fine-grained transfer learning. It first learns domain-invariant features from the source domain to obtain prior

knowledge, and then enriches the target domain discriminative features with the transferred prior knowledge through the gate technique. Extensive offline experimental results on two major e-commerce tasks with real-world datasets as well as in the actual deployment environment demonstrate that PGTL significantly outperforms state-of-the-art transfer learning approaches and can be easily adapted to other tasks. Since its deployment on the Taiwanese portal of Taobao in Aug 2020, it has significantly improved the item exposure rate and item click-through rate for recommended potential items of interest. To the best of our knowledge, this is the first successful deployment of prior guided transfer learning approach in a large-scale e-commerce system.

### Acknowledgements

This research is supported, in part, by Alibaba Group through Alibaba Innovative Research (AIR) Program and Alibaba-NTU Singapore Joint Research Institute (JRI), Nanyang Technological University, Singapore; the National Research Foundation, Singapore, under its AI Singapore Programme (AISG Award No: AISG2-RP-2020-019); NRF Investigatorship Programme (NRFI Award No: NRF-NRFI05-2019-0002); Nanyang Assistant Professorship (NAP); the RIE 2020 Advanced Manufacturing and Engineering (AME) Programmatic Fund (No. A20G8b0102), Singapore. Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not reflect the views of National Research Foundation, Singapore.

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