

# Achieving Lightweight Federated Advertising with Self-Supervised Split Distillation

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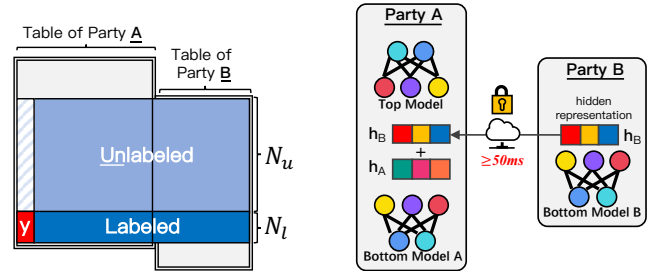
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## Abstract

As an emerging secure learning paradigm in leveraging cross-silo private data, vertical federated learning (VFL) is expected to improve advertising models by enabling the joint learning of complementary user attributes privately owned by the advertiser and the publisher. However, there are two key challenges in applying it to advertising systems: **a) the limited scale of labeled overlapping samples**, and **b) the high cost of real-time cross-silo serving**. In this paper, we propose a semi-supervised split distillation framework **VFed-SSD** to alleviate the two limitations. We identify that: **i) there are massive unlabeled overlapped data available in advertising systems**, and **ii) we can keep a balance between model performance and inference cost by splitting up the federated model**. Specifically, we develop a self-supervised task **Matched Pair Detection (MPD)** to exploit the vertically partitioned unlabeled data and propose the **Split Knowledge Distillation (SplitKD)** schema to avoid cross-silo serving. Empirical studies on three industrial datasets exhibit the effectiveness of our methods, with the median AUC over all datasets improved by **0.86%** and **2.6%** in the local and the federated deployment mode respectively. Overall, our framework provides an efficient solution for cross-silo real-time advertising with minimal deploying cost and significant performance lift.

## 1 Introduction

Immediate personalized auction (such as RTB[Yuan *et al.*, 2014] and the oCPC[Zhu *et al.*, 2017]) is the predominant payment mode in online advertising [Yuan *et al.*, 2013; Google, 2011], where advertisers bid in real-time for every impression or click to show their ads on ad platforms. The bidding price is usually calculated based on the click-through rate (CTR) and the conversion rate (CVR), which are usually estimated by machine learning models trained on data attributes of ads, users, and contextual information. As two key agencies in advertising systems, the advertiser and the publisher (i.e. advertising platforms) own complementary features of user preference. Taking a smartphone user as an ex-



(a) The overlapped samples with timely and clean labels are much fewer than the ones without label ( $N_l \ll N_u$ ).

(b) Online serving of VFL models involves the extra cost of network communication and cross-silo collaboration.

Figure 1: Two challenges of applying VFL in advertising systems.

ample, the advertiser (e.g. a game company) knows his usage and consumption activities on all its own products and the publisher (e.g. a social media platform) knows his browse and click history on all kinds of ads, products and other contents impressed on its platform. Jointly leveraging both two side of these features could provide a more comprehensive understanding of user preference, and produce more precise CTR and CVR models thus improving the profit of both agencies. However, these data can not be directly aggregated due to privacy and intellectual property issues [Voigt and Von dem Bussche, 2017].

As an emerging paradigm for privacy-preserved distributed learning, vertical federated learning (VFL) [Yang *et al.*, 2019b; Kairouz *et al.*, 2021] provides a promising solution for data-sensitive cross-silo business scenarios. Despite its wide application in areas of healthcare and finance [Vepakomma *et al.*, 2018; Ceballos *et al.*, 2020; Webank, a; Webank, b], related explorations have been given less attention to the recommendation and advertising problems [Yang *et al.*, 2020]. We identify that VFL can help advertisers and publishers to leverage their complementary data to train a better joint model while keeping data privately, thus benefiting entities. However, there are two major challenges in applying it to online advertising (as depicted in Figure 1):

- **The limited scale of labeled samples:** Since user preference can experience temporal shifts due to special events, new campaigns, seasonality, and other fac-

tors (e.g., the COVID19), advertising models are often trained on the latest timely data and retrained at a weekly or daily cadence [Muhamed *et al.*, 2022]. While supervised VFL further decreases the scale of available samples, it is only applicable to the labeled overlapping samples between two parties. The two requirements of timely labels and intersected data significantly restrict the volume of training data, which increases the risk of overfitting and especially intensifies the cold-start problem in advertising [Pan *et al.*, 2019].

- **Challenges of cross-silo real-time inference:** A contemporary ad bidding system typically receives million-wise QPS (*query per second*) at peak times [Shen *et al.*, 2015] and its business process including audience identification, auction and ad display, need to be finished in  $10 \sim 100ms$  [Yuan *et al.*, 2014]. Such a strict high throughput and low delay restriction crucially require the high speed of model inference. However, VFL models slow down the inference by taking extra time in encryption and intermediate feature transfer (e.g., network latency typically costs around 50ms [Shen *et al.*, 2015]), let alone the high coordination and operational cost between agencies [Kairouz *et al.*, 2021].

To address these obstacles, we propose the *Vertical Federated Semi-supervised Split Distillation* framework (**VFed-SSD**), which is motivated by:

- **Utilizing unlabeled data:** In advertising dataset, different data attributes shows significantly different temporal shifting cadence [Muhamed *et al.*, 2022], and the label of click or conversion is almost the most volatile and usually noisy [Wu *et al.*, 2022]. Although the outdated samples (due to its outdated label) are discarded in training, we argue that the attributes of these samples are more stable to temporal shifts and contains valuable information. Therefore, we develop a self-supervised task MPD for VFL to exploit the unlabeled federated data to provide a robust initial representation. By extending the learning fashion to semi-supervised learning, we can leverage the massive history data in advertising to enhance the timely updated serving models.
- **Splitting up federated models:** To deploy VFL in current advertising systems with minimal system requirement and achieves the goal of real-time inference, we develop the split knowledge distillation (SplitKD) schema to transfer knowledge from the federated model to local models. The enhanced local model can be deployed independently and does not need any input from another party for inference, thus free from building a cross-silo inference system.

Our contributions can be summarized as follows:

- We develop the first self-supervised pre-training task MPD for vertically partitioned tabular data. It is easy to implement in the VFL environment and performs effectively well. Moreover, its strong association with negative sampling [Levy and Goldberg, 2014] shows its theoretical principle in capturing cross-view correlations by maximizing the pointwise mutual information.

- We design a new federated distillation schema SplitKD that effectively enhances local models and avoids the trouble of deploying split neural networks. It provides a competitive new choice for applying VFL in current real-time ad systems with minimal system requirements, compared to the vanilla cross-silo deployment method.
- The proposed methods are validated on three large advertising datasets (two privates and one open) showing the significant results of  $0.5\% \sim 1.2\%$  improvements on AUC compared to vanilla local models. The private datasets will be publicly available for the hope of promoting related research.

## 2 Related Work

**Federated Learning.** To our knowledge, there is no existing work that accommodates the self-supervised VFL setting for advertising problems, but closely related topics can be found in the setting of horizontal federated learning (HFL), such as HFL for recommendation [Lin *et al.*, 2020b; Muhammad *et al.*, 2020] and semi-supervised learning for HFL [Jeong *et al.*, 2021]. FedMVT [Kang *et al.*, 2020] is the pioneering work of exploring semi-supervised learning in the VFL setting with splitNN-based models [Ceballos *et al.*, 2020]. It proposed to use the non-overlapping data and validated its effectiveness on multi-view image datasets, while our method explores a different scenario of leveraging the unlabeled overlapping samples and tailored for tabular data. Excluding both the HFL setting and VFL setting, FedCT [Liu *et al.*, 2021a] firstly studies the cross-domain recommendation problem in the federated transfer learning setting [Yang *et al.*, 2019a] which requires a solution that is both horizontally separated by sample and vertically separated by attribute domains. However, it is neither suitable for the pure VFL scenario nor capable of leveraging the unlabeled federated data. Besides, these works do not consider the high cost of cross-silo model inference, which is crucial in advertising.

Additionally, another line of work has also put efforts into improving the privacy and security guarantee of the federated learning system [Aono *et al.*, 2017; Liu *et al.*, 2021b; Sun *et al.*, 2021; Jin *et al.*, 2021], especially the problem of label leakage [Liu *et al.*, 2021c; Fu *et al.*, 2022; Sun *et al.*, 2022; Yang *et al.*, 2022]. These ideas are complementary to ours and can be combined to enhance security, so we focus on the aspect of model training in this paper.

**Unsupervised Pre-training.** The deep pre-trained model has recently achieved remarkable success in natural language processing and computer vision [Devlin *et al.*, 2018; Liu *et al.*, 2019; Clark *et al.*, 2020] and is also making progress in recommendation (such as the Correlated Feature Masking technique [Yao *et al.*, 2021]), but they are all limited to the context of centralized machine learning. Some technics like contrastive learning were also adopted in federated learning [Dong and Voiculescu, 2021], but only for the HFL and image data, instead of the VFL setting and categorical tabular data. It is still an open challenge to use extensive unlabeled tabular data for vertical federated learning. While in this paper, we take the first attempt to develop a self-supervised task MPD for vertically partitioned tabular data.

**Knowledge Distillation.** Knowledge distillation (KD) [Hinton *et al.*, 2014] is widely applied to solve the model aggregation problem in HFL [Li and Wang, 2019; He *et al.*, 2020; Lin *et al.*, 2020a]. These works require the input fields of the student and teacher must be identical. While our framework is significantly different, only part of the input field of the teacher is accessible to a student. From another viewpoint, This fashion can also be regarded as leveraging privileged information, as in [Vapnik and Vashist, 2009; Vapnik *et al.*, 2015; Xu *et al.*, 2020] and a concurrent work [Ren *et al.*, 2022]. However, we further consider the problem with unsupervised pre-training and tailor our method for VFL tasks in particular. Overall, our final student model can leverage cross-domain correlation from both labeled and unlabeled data and is capable of making predictions independently.

### 3 Method

#### 3.1 Preliminaries

**Problem Setting** We focus on a typical two-party vertical federated learning problem where an *active party* holding the label and some attributes collaborates with a *passive party* who provides additional attributes to train a federated model. We consider both the CVR and CTR prediction problems in this scenario. Since the label is usually the key asset of the active party and is highly sensitive, the passive party is not allowed to access the final prediction model (due to the label inference attack [Fu *et al.*, 2022]). They usually ask for money in return and do not need the final prediction model. In the special case of CTR prediction, the passive party also has the same label information so that has the right to access the final model. But in practice, usually, the active party is the only party who deploys the model, so we focus on discussing the active party’s benefit in the following sections for brevity. Results for the passive party are analogous.

**Backbone Model** Inspired by vertical split learning [Vepakomma *et al.*, 2018; Ceballos *et al.*, 2020], we implement VFL by adopting a specific *Two-party Vertical SplitNN* schema without the third-party coordinator. The federated model consists of the *bottom model* and the *top model*. As shown in Figure 1b, each party holds a bottom model and the active party additionally holds a top model. Let’s use  $A$  to denote the active party and use  $B$  to denote the passive party. For conciseness, all the input attributes from a party are denoted as a vector  $\mathbf{x} \in \mathcal{R}^d$ , comprised by the concatenation of categorical embedding vectors and numerical values. Thus, the complete federated model can be denoted as a composite function of partial models:

$$\hat{y} = g_A(f_A(\mathbf{x}_A), f_B(\mathbf{x}_B)),$$

where  $f$  denotes the bottom model,  $g$  denotes the top model. The subscripts  $A$  and  $B$  denote the location of the functions. To finish the forward propagation, the hidden output  $\mathbf{h}_B = f_B(\mathbf{x}_B)$  of party  $B$  is sent to party  $A$  for the subsequent computation of  $g_A$  and loss function; For the backward propagation, the gradient of loss over  $\mathbf{h}_B$  is sent to party  $B$  for the subsequent gradient computation for  $f_B$ . The transmission process can be combined with encryption techniques to enhance security, as we mentioned in section 2.

#### 3.2 Self-Supervision for Partitioned Attributes

**Task Description:** Notably, in a vertical federated dataset, every sample essentially meets the condition of “alignment” and “multi-view”. Motivated by this, we propose the matched pair detection (MPD) task to exploit this kind of self-supervised signal of multi-view sample matching. It aims to learn a binary classifier capable of distinguishing whether the input attributes from two parties are matched. To do so, we treat an original paired sample as a positive sample and replace its correctly paired half with a randomly sampled wrong half to construct a negative sample.

**Batch-wise Objective:** For an efficient implementation free from full-scale preprocessing, we dynamically perturb samples in each batch. Let’s use  $\mathbf{X} \in \mathcal{R}^{m \times d}$  to denote a batch of unlabeled inputs from a single party, then a complete positive batch for pre-training can be denoted as a concatenated matrix of two partial batches  $\mathbf{U}^+ = [\mathbf{X}_A; \mathbf{X}_B]$ . Each row in  $\mathbf{U}^+$  is a correct pair  $(\mathbf{x}_A^i, \mathbf{x}_B^i)$  observed in the dataset, with the label assigned as  $y_u^i = 1$ . For each positive batch, We construct a corresponding negative batch by left-multiplying a random *row-permutation matrix* [Wikipedia, 2022] to the target half of the positive batch, such that  $\mathbf{U}^- = [\mathbf{P}\mathbf{X}_A; \mathbf{X}_B]$ , where  $\mathbf{P} \in \mathcal{R}^{m \times m}$  is restricted to hold a zero diagonal. The perturbation (i.e., sampling) is guided by the number of times the input vector appears in the local batch, as a coarse estimation of its global distribution in the whole dataset. This kind of distribution is analogous to the “unigram” distribution in language models [Levy and Goldberg, 2014]. Such perturbation does not involve additional cross-silo coordination and can be efficiently implemented by matrix multiplication operations, which is very friendly for industry cross-silo scenarios. The model is finally trained with both the positive and negative batches:

$$\mathcal{L} = \vec{\mathbf{1}} \cdot [\log \sigma(g(\mathbf{U}^+)) + \log \sigma(-g(\mathbf{U}^-))]^\top \quad (1)$$

Here  $g$  is short for the complete federated model. Once the pre-training is finished, only the bottom models  $f_A$  and  $f_B$  are used as initialization in fine-tuning or distillation.

**Theoretical Analysis:** Despite its conciseness in implementation, we are also curious about the intrinsic learning principle of MPD. Considering the MPD task is trying to maximize  $P(y_u = 1 | \mathbf{x}_A, \mathbf{x}_B)$  for correct pairs while maximizing  $P(y_u = 0 | \mathbf{x}_A^*, \mathbf{x}_B)$  for randomly sampled “negative” samples. We can re-write the learning objective for a distinct matched pair  $(\mathbf{h}_A^i, \mathbf{h}_B^i)$ :

$$\begin{aligned} \mathcal{L}_i &= \log \sigma(g_A(\mathbf{h}_A^i, \mathbf{h}_B^i)) \\ &+ k \cdot \mathbb{E}_{\mathbf{h}_A^* \sim P_D} \log \sigma(-g_A(\mathbf{h}_A^*, \mathbf{h}_B^i)) \end{aligned} \quad (2)$$

where  $\sigma(\cdot)$  is the sigmoid function and  $k$  is the number of “negative” samples,  $\mathbf{h}_A^* = f_A(\mathbf{x}_A^*)$  is the hidden representation of a sampled negative half  $\mathbf{x}_A^*$ , drawn from the empirical “unigram” distribution  $P_D(\mathbf{h}_A) = P_D(\mathbf{x}_A) = \frac{\#(\mathbf{x}_A)}{|D|}$ . Here  $\#(\mathbf{x}_A)$  denotes the number of times  $\mathbf{x}_A$  appears in the dataset  $D$ . If we analogously treat  $\mathbf{h}_A$  and  $\mathbf{h}_B$  as a word embedding  $\vec{w}$  and its context embedding  $\vec{c}$  in word2vec [Mikolov *et al.*, 2013], we can find that our equation (2) is similar to equation (1) of [Levy and Goldberg, 2014]. The only difference is the

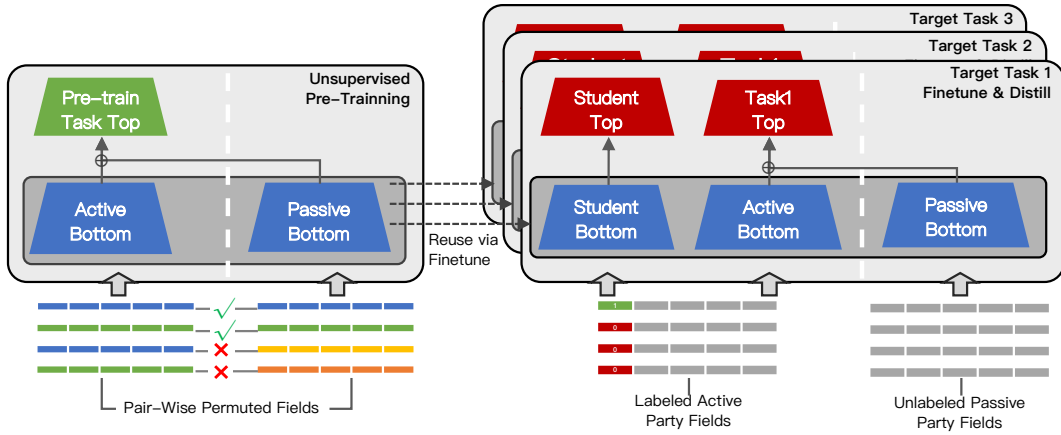


Figure 2: The overall framework of VFed-SSD . The left part shows the pre-training process of MPD and the right shows the process of federated knowledge transfer. During pre-training, the two parts of an unlabeled sample are permuted to construct mismatched pairs, depicted as mismatched colors. During distillation, both the teacher and student are initiated with pre-trained bottom models.

choice of similarity function where we use  $g_A$  and they use dot-product. Analogously replacing  $\vec{w} \cdot \vec{c}$  in their equation with  $g_A(\mathbf{h}_A, \mathbf{h}_B)$ , we can get a similar revelation as in [Levy and Goldberg, 2014]:

$$g_A(\mathbf{h}_A, \mathbf{h}_B) = PMI(\mathbf{x}_A, \mathbf{x}_B) - \log k. \quad (3)$$

That is to say, the top model implicitly models the point-wise mutual information (PMI) of the observed input pairs, with a shifted constant  $\log k$ . Specifically, when  $k = 1$ , the learning process of MPD encourages maximizing the mutual information between the hidden representations of two parties. This learning principle of maximizing (shifted) mutual information strongly supports the MPD pre-training task to learn good cross-view representations. Due to the page limit, we omit the proof and suggest readers refer to [Levy and Goldberg, 2014] for more detail.

### 3.3 Partial Knowledge Transfer

How could we avoid the high costs of serving the vertical splitNN across silos while preserving the benefits of connecting data silos? We propose a feasible solution of “semi-federation” that combines party-coupled federated training and party-independent local inference. Specifically, we develop the Split Knowledge Distillation (SplitKD) scheme to transfer knowledge from the federated teacher model to a local student model. The student model is decoupled with the federation while keeping advantages over the vanilla local model with no federation. Its structure can be further simplified to achieve faster online inference. Let’s use superscript  $T$  and  $S$  to denote the functions of the teacher and the student respectively, taking the student of party A as an example, the process of model splitting can be formalized as follow:

$$\hat{y}_A = g_A^S(f_A^S(\mathbf{x}_A)), \hat{y}_{Fed} = g_A^T(f_A^T(\mathbf{x}_A), f_B^T(\mathbf{x}_B)) \quad (4)$$

$$\mathcal{L}_A^S = \alpha \cdot CE(y, \hat{y}_A) + (1 - \alpha) \cdot KL(\hat{y}_{Fed}, \hat{y}_A) \quad (5)$$

where  $\hat{y}_{Fed}, \hat{y}_A$  denote the predictions,  $y$  is the ground-truth label from party A.  $g_A^S$  and  $f_A^S$  denote the top part and bottom part of the student.  $KL(\cdot)$  denotes the KL divergence and

$CE(\cdot)$  denotes the binary cross-entropy loss. We use  $\alpha$  as a hyper-parameter to balance the effect of raw label and the federated soft label.

Once the distillation is finished, the student model can be independently deployed to existing local inference systems, without any additional system requirements. We emphasize that *the deployment of our student model is the same as a traditional local real-time model*, as long as the current inference system works in real-time (which is already satisfied), we can naturally meet the real-time requirement only by adopting the same model architecture in the student model.

## 4 Experiments

We conduct experiments to answer three research questions about our framework:

- (Q1) How much does the vanilla vertical federated model outperforms local models?
- (Q2) How much does the vanilla vertical federated model benefits from massive unlabeled data?
- (Q3) How much does the local model benefit from VFL, when both the labeled and unlabeled data are used?

Q1 and Q2 focus on the effectiveness of VFL and our self-supervised task MPD without considering the cost of building a federated real-time inference system. While Q3 is the most important question we are concerned that how much can we still benefit from VFed-SSD when a federated real-time bidding system is not feasible (or cost too much), whether the enhanced local models outperform vanilla local models? Note that comparing an enhanced model with its corresponding federated model is unfair, as almost half of the features are missed, which is expected to incur a drop in performance. From a realistic viewpoint, we pursue the goal that the enhanced local models can outperform vanilla local models and set the performance of the federated model as an upper bound.

Table 1: Dataset statistics information and model structure. **M** indicates million and **K** indicates thousand. "**#fields**" denotes the number of data fields and "**#dim**" denotes the total dimension of the input features after hash embedding, they are both represented by two segmented numbers, each corresponding to one federated party.

Item	Game-Ad	Game-Social	Criteo-NC
#no label	5M	5M	5M
#labeled	640K	360K	1.5M
#test	25K	50K	0.5M
positive%	1:13	1:20	1:40
#fields	51   27	89   39	13   26
#dim	2122   1017	166   298	13   260
bottom-A	64 → 64	64 → 64	32 → 32
bottom-B	64 → 64	64 → 64	128 → 64
top	64 → 64	64 → 64	64 → 64

## 4.1 Datasets

We collect two real federated datasets from Tencent, "the world's largest video game publisher" called by the Economist [Economist, 2020]. They are inherently vertically partitioned, multi-viewed, and privacy-sensitive. We also use a well-known public dataset from Criteo [CriteoLabs, 2014] and manually partition its attributes to simulate a vertical federated data setting. Details are summarized in Table 1.

**1. Game-Ad CVR Dataset.** This dataset comes from Tencent game and a major advertising platform. The active party provides the label of game account registration and user features extracted from users' behavior history in more than 100 games, while the passive party provides features such as users' profile, purchase level, and activity degree in all kinds of products and media.

**2. Game-Social CVR Dataset.** This dataset comes from Tencent game and a major social media platform. The social media platform provides rich user portrayals extracted from massive social behaviors. The task is also to predict the conversion rate of users for game ads, but for multiple games.

**3. Criteo-NC CTR Dataset.** Criteo is a public CTR benchmark dataset. We manually split its fields into the **Criteo-Numerical** part and the **Criteo-Categorical** part for the active and passive parties, respectively.

## 4.2 Baselines and Model Settings

We validate our method in two settings: *the federated serving* setting and *the local serving* setting. The former assumes that a real-time federated inference system is available and the latter assumes not. Specifically, two parties conduct online serving by independently deploying their local model in the local setting but collaboratively deploying a federated model in the federated setting.

**The federated setting:** We set 3 methods to validate the advance of leveraging unlabeled data and the efficiency of our pretext task MPD. **(1) VFL:** The vanilla VFL setting. **(2) VFL-ST:** We adopt a practice method usually called self-training [Blum and Mitchell, 1998; Nigam and Ghani, 2000; Rosenberg *et al.*, 2005] to leverage federated unlabeled data, as a baseline to compare with our MPD task. Specifically,

a federated model pre-trained on the labeled data is used to produce soft labels on the unlabeled data, then a new model is trained with these soft labels. **(3) VFL-MPD:** We train a federated model on the unlabeled data with the objective of MPD, and then finetune it on the labeled data.

**The local setting:** We set 4 methods to validate the effectiveness of the overall framework VFed-SSD and the performance contributions of MPD and SplitKD: **(1) Baseline Local:** A simulation scenario without using federated learning where each party trains a local model. The ground truth label is assumed to be shared with the passive party for simulation. **(2) Local-MPD:** The training of local models is similar to "Baseline Local", except that: a) the local bottom model is initialized with its corresponding bottom part in a federated model pre-trained by MPD. b) The bottom part is finetuned. It's a simplified variant of VFed-SSD to inspect the contribution of MPD. **(3) Local-SD:** The local models are acquired by splitting up a federated model trained on the labeled data. It's referred to inspect the contribution of SplitKD to VFed-SSD. **(4) Local-SSD:** This is the complete version of our method. Compared to SplitKD, the federated teacher is additionally pre-trained on the unlabeled data via MPD.

Following related works in advertising [Guo *et al.*, 2017], we use AUC (Area Under the ROC curve) as the evaluation metric. The architecture details of our backbone model are shown in Table 1. We use the Adam optimizer with  $L_2$  regularization to avoid overfitting. The batch size is 10K and 5K for the pre-training task and downstream tasks respectively. We use 1/20 of training data as the validation set to conduct early stopping. We tune hyper-parameters for all methods and report the best result among 3 repeated runs for each. The main and fine-tune learning rates are chosen in  $\eta \in \{1^{-2}, 5 * 1^{-3}\}$ ,  $\eta' \in \{1^{-3}, 5 * 1^{-4}\}$ , and the distillation weight  $\alpha \in \{0.5, 0.9\}$ , and the  $L_2$  penalty coefficient  $\lambda \in \{1^{-4}, 1^{-5}\}$ . All experiments are conducted via the FL platform PowerFL[Tencent, 2020](with a Tensorflow backend [Abadi *et al.*, 2015]).

## 4.3 Results and Analysis

### Validity of Vanilla VFL

Although VFL sounds promising, it does not always improve performance in practical (as results of vanilla-VFL shown in [Kang *et al.*, 2020]), due to feature efficiency and segmented network architecture. So we first check whether this fundamental requirement is satisfied with our dataset and backbone model. The difference in feature quality between the two participants naturally leads to unbalanced model performance (as details shown in line one of Table 3). As shown in Table 2, VFL significantly outperforms local models of the active party on all three datasets, thus we answered question **Q1**. The significantly higher performance lift on the Criteo-NC dataset is reasonable, for the active party uses only 13 of 39 total attributes.

### Advantages of Self-Supervised Pre-training

As shown in Table 2, the two methods using the unlabeled data get further improvements over vanilla VFL. Besides, our MPD task outperforms "VFL-ST" by additional **0.98%**, **0.19%**, and **0.38%** points on three datasets, respectively. It

Table 2: Results on the *federated setting*. It shows that the vanilla VFL outperforms local models in all the datasets and our self-supervised task consistently outperforms all the baselines. “↑” denotes the absolute AUC improvements compared to the baseline. “U” denotes the use of unlabeled data. Terms in bold with blue denote the best.

Method	U.	<i>Game-Ad</i>		<i>Game-Social</i>		<i>Criteo-NC</i>	
		AUC%	↑	AUC%	↑	AUC%	↑
Baseline Local	✗	70.78	—	70.64	—	68.30	—
VFL	✗	72.12	1.34	72.98	2.34	75.94	7.65
VFL-ST	✓	72.32	1.55	73.11	2.48	76.71	8.41
<i>Ours (VFL-MPD)</i>	✓	<b>73.30</b>	<b>2.53</b>	<b>73.31</b>	<b>2.67</b>	<b>77.08</b>	<b>8.79</b>

‰: values are shown in percentage for readability.

Table 3: Results on the *local setting*. Our method achieves the best result and its two simplified variants also significantly outperform the baseline, indicating the validity of its two components.

Method	U.	<i>Game-Ad</i>		<i>Game-Social</i>		<i>Criteo-NC</i>	
		AUC%	↑	AUC%	↑	AUC%	↑
Baseline Local	✗	70.78	—	70.64	—	68.30	—
Local-SD	✗	71.01	0.23	71.55	0.91	68.73	0.43
Local-MPD	✓	70.79	0.02	71.33	0.69	68.65	0.35
<i>Ours (Local-SSD)</i>	✓	<b>71.67</b>	<b>0.89</b>	<b>71.87</b>	<b>1.23</b>	<b>68.77</b>	<b>0.47</b>

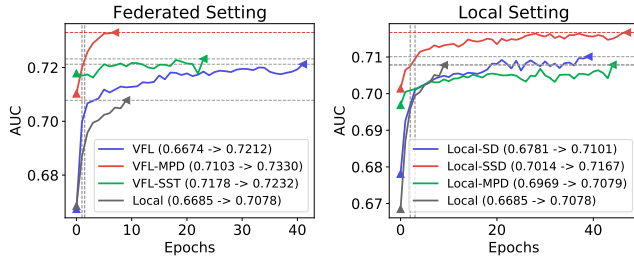


Figure 3: Advantages of MPD. With pre-training by MPD, models can achieve the same AUC performance with outstanding fewer training epochs on both experiment settings. The final performance also significantly outperforms the others.

indicates that MPD can use unlabeled data more efficiently and learns better representation, thus we answered question Q2. Specifically, as shown in Figure 3, methods equipped with MPD achieve the best performance at the endpoint and achieves the second-best performance at very early epochs. Besides, they also provide a higher starting point in most cases. Though “VFL-ST” provides a higher point in the federated setting, its best performance is significantly lower than ours, revealing its limitation in mining self-supervised knowledge. Moreover, considering that the pre-training process of “VFL-ST” used the same label information as in the fine-tuning process, a higher initial point is under expectation. All the values in Figure 3 are calculated on the validation set, starting from the first epoch, and ending at the epoch with the best performance (identified by early stopping). Due to the page limit, we only pick the Game-Ad dataset as an example.

### Advantages of Partial Knowledge Transfer

In the setting of local serving, our focal point is the performance of the active party and its improvement achieved by

other methods. We evaluate all methods by the absolute AUC improvement over the vanilla local model. As shown in Table 3, our method significantly improves the local performance with **0.89%**, **1.23%** and **0.47%** over three datasets, respectively. The superior performance gives us a sufficient reason to replace the local vanilla model as the student model to conduct online serving. Notice that, the gap between “Local-SD” and “VFL” is natural, as the set of available features for local models is significantly smaller than for the federated model, as depicted in the middle part of Table 1. We also conducted an ablation study to test the efficacy of the two components of our method. As shown in Table 3, both “Local-SD” and “Local-MPD” significantly outperform the local baseline, but are weaker than “Local-SSD”. This suggests that the two components are efficient and can achieve better performance when combined. Thus we answered question Q3.

## 5 Conclusion and Future Work

In this paper, we propose a semi-supervised VFL framework VFed-SSD for cross-silo display advertising. We highlight the existence of massive unlabeled overlapping data in advertising and develop a self-supervised task MPD to exploit its potential in representation learning. Meanwhile, we develop a novel knowledge transfer schema SplitKD to meet the strict system response time restriction of advertising systems. Experiments on real industrial datasets show that our method can significantly improve performance. Despite our focus in advertising, our methods are also suitable to other tabular-data-based VFL tasks and can be naturally extended to the multi-party scenario. We are now testing our framework in online advertising business of Tencent Game to evaluate its effect on final profits. We also plan to further enhance its security, integrate cutting-edge advertising models, and explore its flexibility to larger-scale datasets.

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