Vertical Semi-Federated Learning for Efficient Online Advertising

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Abstract
The traditional vertical federated learning schema suffers from two main issues: 1) restricted applicable scope to overlapped samples and 2) high system challenge of real-time federated serving, which limits its application to advertising systems. To this end, we advocate a new learning setting Semi-VFL (Vertical Semi-Federated Learning) to tackle these challenge. Semi-VFL is proposed to achieve a practical industry application fashion for VFL, by learning a federation-aware local model which performs better than single-party models and meanwhile maintain the convenience of local-serving. For this purpose, we propose the carefully designed Joint Privileged Learning framework (JPL) to 1) alleviate the absence of the passive party’s feature and 2) adapt to the whole sample space. Specifically, we build an inference-efficient single-party student model applicable to the whole sample space and meanwhile maintain the advantage of the federated feature extension. New representation distillation methods are designed to extract cross-party feature correlations for both the overlapped and non-overlapped data. We conducted extensive experiments on real-world advertising datasets. The results show that our method achieves the best performance over baseline methods and validate its superiority in the Semi-VFL setting.

Table 1: The spectrum of different VFL settings. Semi-VFL maximizes data utilization and supports local deployment. (p denotes the distribution for the full sample space while q denotes the one for the overlapped sample space. $D_A$ is the subset of $D_{full}$ owned by the active party.)

| Setting | No-VFL | Semi-VFL | Full-VFL |
|---------|--------|----------|----------|
| Distribution | $p(y|x_A)$ | $p(y|x_B)$ | $q(y|x_A, x_B)$ |
| Data Scope | $D_A$ | $D_{full}$ | $D_{fed}$ |
| Training Input | $x_A$ | $x_A, x_B$ | $x_A, x_B$ |
| Test Input | $x_A$ | $x_A$ | $x_A, x_B$ |
| Local Inference | ✓ | ✓ | ✓ |

1 Introduction
Immediate auction (such as RTB [Yuan et al., 2014] and the oCPC [Zhu et al., 2017]) is the predominant trading mode of online advertising, where advertisers bid in real-time for every individual impression of the ad platform. The bidding price and the final ad ranking are both deeply influenced by the click-through rate (CTR) and the conversion rate (CVR). They have direct impacts on the final revenue for both entities and play key roles in advertising systems. User modeling is key to accurate CTR and CVR estimation, which need lots of action data from both the advertiser and the platform. As two core roles in the advertising system, user features collected

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• **High cost in decentralized serving:** Compared to single-party models, the inference process of VFL models brings extra time costs (caused by cross-agency feature transmission and security enhancement operations) and poses new system design challenges (due to the inconsistent network conditions and computational power of different parties). Such complex conditions are acceptable for offline model training but nearly infeasible for online model inference, since the federated inference system must meet the high throughput and real-time latency requirements of advertising systems (million-wise peak QPS, 10 ~ 100ms process time per request [Shen et al., 2015; Yuan et al., 2014]). These obstacles may cause the federation infeasible or cost too much.

To overcome these disadvantages, we investigate a new learning paradigm that requires the participant to jointly utilize both the overlapped and non-overlapped samples but meanwhile be rid of decentralized model inference. We term this learning fashion as “Semi-VFL” (Vertical Semi-Federated Learning), since only the training involves distributed communication and the inference doesn’t. Analogously, we identify the original VFL setting as “Full-VFL” and the unilateral-party learning setting as “No-VFL”. We advocate Semi-VFL as a lightweight and practical problem setting to reap the benefits of data field expansion. It is more efficient than No-VFL for better performance, and lighter than Full-VFL for easy deployment. Notably, there are two key points in designing a good solution for Semi-VFL:

- **Alleviating field missing:** Only the overlapped samples have additional attributes from the passive party, and even though, they are banned to use in the inference stage. Maintaining and generalizing knowledge implied in these attributes is challenging but crucial for Semi-VFL to outperform No-VFL.

- **Adapting whole sample space:** The final test samples come from the whole sample space, and only the active party’s data attributes are available. Compared to Full-VFL, it’s important for Semi-VFL to jointly consider both the overlapped and non-overlapped sample distribution to learn a comprehensive model.

To achieve both goals, we propose a **Joint Privileged Learning framework (JPL)** to learn a single-party model reaps the privileged knowledge of the federated model and the non-overlapped data to make better predictions for the whole sample space, but only conditioned on the active party’s feature space. Specifically, we use both the overlapped and non-overlapped samples in an End2End fashion to consider the whole sample distribution, and explicitly learns the correlation between two-party’s feature space to maintain federated knowledge. Our contributions can be summarized as follow:

1. **We identify the vertical semi-federated learning setting for advertising systems as an important research problem due to its wide application in industrial scenarios.**

2. **We propose an effective distillation framework JPL to implement Semi-VFL and achieves expected results.**

3. **We conducted extensive experiments on benchmark datasets and validate the superiority of our method over baselines.**

## 2 Preliminary

### 2.1 Two-Party Vertical SplitNN

VFL enables multiple participants (usually two) to collaboratively train a machine learning model with features distributed among them but labels owned by only one of them. The label owner party is called the active party, and the others are passive parties. 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., 2022a]). Thus, the typical target of building a vertical federation is to improve the performance of the active party. Only the active party is willing and granted to deploy the model and the passive party only charge for data usage.

In advertising systems, we have only two participants and the predominant model structure is neural networks. So in this paper, we focus on a typical two-party VFL setting and use the SplitNN [Vepakomma et al., 2018; Ceballos et al., 2020] as the backbone model. For the sake of brevity, we use the term “local” as a special pronoun for the active party in the following sections. In splitNN, each party holds a bottom model for extracting hidden representations and the active party additionally holds a top model to fuse two sides of representations and make predictions. The fusion layer is called the cut layer and is usually implemented by concatenation. To finish the training, the passive party will send its hidden representations to the active party in the forward process, and receive gradients from the active party in the backward process. The security of intermediate data transmission can be satisfied by combining methods proposed by related works which are complementary to us, so we focus on the aspect of model training.

As common industrial choices, we use the hash embedding layer to process the categorical input fields and MLP for both the bottom and top models. However, our method is not restricted to these choices and is applicable to more complex and advanced structures. Using A and B to denote the active party and the passive party respectively, the federated model can be denoted as:

$$\hat{y} = g_A([f_A(e_A), f_B(e_B)])$$

where $e_A = [e_A^1, e_A^2, \ldots, e_A^{m_A}]$ and $e_B = [e_B^1, e_B^2, \ldots, e_B^{m_B}]$ are wide concatenated vectors of all fields’ embedding vectors, $m_A$ and $m_B$ denote the number of input fields. $f_A$ and $f_B$ are bottom models, $g_A$ is the top model and $\hat{y}$ denotes the prediction. Besides, We’ll use $h_A = f_A(e_A), h_B = f_B(e_B)$ to denote the hidden representations for the overlapped data, and $u_A = f_A(e_A'), u_B = f_B(e_B')$ for the non-overlapped data.

### 2.2 Problem Formulation

Given the full labeled dataset $D^\text{full} = \{D_A^{\text{fed}}, D_A^{\text{loc}}\}$ composed by the overlapped part $D_A^{\text{fed}} = \{X_A^{\text{fed}}, Y_A^{\text{fed}}\}$ and the non-overlapped part $D_A^{\text{loc}} = \{X_A^{\text{loc}}, Y_A^{\text{loc}}\}$, the aim of
Semi-VFL is to learn a function \( s(x_A) \) to model \( p(y|x_A) \) by fully utilizing \( D^{full} \), where \( p(y|x_A) \) is the conditional label distribution regarding to the active party’s feature. The core goal of Semi-VFL is to achieve better results than No-VFL while relying only on active party features. Compared with traditional settings (as shown in table 1), the advantages of Semi-VFL can be summarized as follows:

1. Semi-VFL extends the applicable scope of Full-VFL from the overlapped sample space to the full sample space, but do not rely on knowing the passive party’s feature.
2. Semi-VFL can utilize more data than both No-VFL and Full-VFL, but maintains the same level of inference cost as No-VFL.

3 Method
3.1 The Overall Framework
JPL is designed as a two-stage learning framework: the federated pre-learning stage and the JPL stage, as shown in Figure 1. The first stage learns \( q(y|x_A, x_B) \) from the overlapped data, and the second stage jointly uses all data to learn a student model aware both to the federated distribution \( q(y|x_A, x_B) \) and the local distribution \( p(y|x_A) \). During the JPL stage, the teacher model is fixed and acts as a regularizer to constrain features and predictions of the student. Once the JPL stage finished, all the auxiliary modules will be dropped and the inference of the student model is decoupled with the passive party. Compared with the vanilla splitNN, our method do not involves new security problems. It do not add new procedures in federated training and thus do not involves additional network transmission requirements and new security risks. In other words, the security level of our method is the same as splitNN, existing security enhancement methods for splitNNs are also applicable to our approach.

3.2 Model Structure
Let’s firstly unify the notations. Bottom models are denoted as \( f \) and top models are denoted as \( g \), here the top model may take one or more hidden representations from party A or party B as inputs. The superscript \( T \) and \( S \) identify whether a function belongs to the teacher or the student. The subscripts \( A \) and \( B \) denote a function’s functionality in processing specific feature space, not its physical affiliation. As for model affiliation, among all parameterized functions and embedding, only \( f^A_1 \) and \( e^B_1 \) belong to the passive party.

As shown in figure 1 the student model has two bottom modules and three top modules during training. The two bottom modules \( f^A_1 \) and \( f^B_1 \) uses \( x_A \) to respectively learn hidden representations for \( x_A \) and \( x_B \). \( g^A_1, g^B_1 \) and \( g^{Fed}_F \) are three classifiers respectively working in the feature space of party A, party B and both. Note that, these modules can take in both the overlapped and non-overlapped samples as input. All prediction results produced by classifiers will used together with the teacher’s predictions to form the JPL loss. After JPL training, the auxiliary classifier \( g^B_1 \) will be dropped, the final prediction is the ensemble of the rest classifiers.

3.3 Imitating Full Feature Space
The performance improvement of the federated model is brought by the additional use of B-side features, but they are banned to use in the inference stage of Semi-VFL, this seems to be an insoluble paradox. So how can we still leverage the knowledge of \( x_B \) to make predictions, with only \( x_A \) available? From a probabilistic view, the only possible way is to learn the intrinsic correlation between \( x_A \) and \( x_B \) (e.g., the conditional distribution \( p(x_B|x_A) \)). And fortunately, the B-side feature for the overlapped samples is available during the training process. Based on these motivations, we design a partial encoder \( f^B_2(x_A) \) to learn the mapping function from the A-side input space to the B-side feature space. Since there is no available B-side feature for the non-overlapped data, we firstly learn from the overlapped part and further transfer its knowledge to the non-overlapped part. For the partial encoder, we expect its output features can imitate the functionality of raw ones, it can be described from two aspects:

- **equivalence in feature representation**: In the ideal case, we expect imitation features to be numerically equal to the original features, but this is difficult and unrealistic due to the intrinsic difference of A and B, so we only require to maximize their similarity in some transformed space as a looser constraint. As a common and practical choice, we use the same measurement as in CL, that is cos-similarity or dot-product in the vector \( L_2 \) hypersphere.
- **equivalence in label discrimination**: the imitation feature
should manifest the same discriminative functionality as the raw one, including its cooperative discriminative utility in the federated classifier \(g_{Fed}^T(\cdot)\) and the independent discriminative utility in the B-side classifier \(g_B^T(\cdot)\). These two classifiers have different inductive biases, so we take both of them into consideration to promote a comprehensive modeling.

**For the Overlapped Sample**

Let's use \(h_B^S = f_B^S(x_A), \forall x_A \sim q_o(x_A)\) to denote the imitation feature of samples from the overlapped distribution \(q_o(x_A)\). For the representation equivalence, we design the cross-correlation matrix error (CME) to reconstruct the similarity of B-side features. Firstly, the features are transformed to a metric space and measured by cosine similarity:

\[
sim(h_B^S, h_B^T) = \frac{r(h_B^S) \cdot r(h_B^T)^T}{\|r(h_B^S)\|_2 \|r(h_B^T)\|_2}
\]

where \(r\) is a shared projection function. To be succinct, we use \(s = r(h_B^S)/\|r(h_B^S)\|_2\) and \(t = r(h_B^T)/\|r(h_B^T)\|_2\) as abbreviation of the transformed features, respectively. Using the matrix \(S \in \mathbb{R}^{N \times d}\) and \(T \in \mathbb{R}^{N \times d}\) to denote a batch of \(N\) features in the metric space for the student and teacher, the cross-correlation error matrix is \(C = S \cdot T^\top - T \cdot T^\top\), where \(c_{ij} = s_i \cdot t_j^\top - t_i \cdot t_j^\top\). Regarding to the importance of negative student-teacher pairs and labeled negative samples, we can write three version of CME: CME, single-balanced CME(bCME) and double-balanced CME (dCME), as show in follow:

\[
\mathcal{L}_{CME} = \frac{1}{N^2} \|C\|_F^2
\]

\[
\mathcal{L}_{bCME} = \frac{1}{N} \|\text{diag}(C)\|_2^2 + \frac{1}{N(N-1)} \|C - \mathbf{I}\|_F^2
\]

\[
\mathcal{L}_{dCME} = \sum_{i \in [Y^+, Y^-]} \frac{1}{|T|} \sum_{t \in T} (c_{it}^2) + \frac{1}{N-1} \sum_{j \in Y} c_{ij}^2
\]

where \(Y^+\) and \(Y^-\) denotes the index sets of the positive and negative samples, \(|\cdot|\) denotes the cardinality. \(N\) denotes the batch size, \(I\) is the identity matrix and \(\text{diag}(\cdot)\) means the diagonal vector of a matrix. The original CME treats all similarity pairs with equal importance, while the bCME balance the importance of the correct and incorrect student-teacher pair. The dCME further consider the skewness of binary label. The degree of “balance” between the three losses gradually increases. The so-called “balance” takes into account two facts: 1) positive labels are scarce and more important than negative labels, and 2) the right pair is scarce and more important than the wrong pair. We choose dCME as the B-side feature reconstruction loss.

For the discrimination equivalence, we just constrain the predictions of the imitated features to be close to the true ones. The discrimination equivalence is defined as:

\[
\mathcal{L}_{de}^o = \alpha \cdot KL(g_{Fed}^T(h_A^S), h_B^T) + KL(g_B(h_B^S)||g_B(h_B^T)) + \sum_{h \in \{h_B^S, h_B^T\}} \text{CE}(y, g_B(h))
\]

where \(CE\) denotes the binary cross-entropy loss, \(KL\) is the KL-divergence and \(\alpha\) is a hyper-parameter controlling the loss effect of the federated teacher. Finally, we sum up above two losses as the “A to B” transformation loss for the overlapped data:

\[
\mathcal{L}_{a2b}^o = \mathcal{L}_{dCME} + \mathcal{L}_{de}^o
\]

**For the Non-overlapped Sample**

Let's use \(u_B^S = f_B^S(x_A)\) to denote the imitation feature of samples \(x_A \sim q_o(x_A)\) from the non-overlapped distribution. Due to the absence of corresponding ground-truth from the teacher (\(u_B^T\) do not exist), we can not directly learn B-side feature information for the non-overlapped data. Motivated by the principle of collaborative filtering (CF) [Koren et al., 2012], we propose the cross-space similarity isomorphic (CSI) loss to transfer the B-side knowledge from the overlapped data to the non-overlapped data. CF assumes that similar users prefer the same items, i.e., if two users are similar in the user feature space, then they should also be similar in the item space. CSI inherits this principle, it assumes that the similarity of samples in both feature space A and B should be numerically close or equal (so-called isomorphic). Based on CSI assumption, we can use the A-side similarity between the overlapped samples and the non-overlapped sample to guide the learning of \(u_B^S\). Respectively using capital letter \(U\) and \(H\) to denote a batch of \(N\) features (with \(L_2\)-normed) from \(q_n\) and \(q_o\), the CSI loss is:

\[
\mathcal{L}_{csi}^n = \|c(U_A^S \cdot H_A^S, \tau) - c(U_B^T \cdot H_B^T, \tau)\|_F^2
\]

where \(c\) denotes the softmax function with a temperature parameter \(\tau\). Here we select the teacher’s feature space as the anchor space, for \(U_B^T\) to achieve the purpose of feature imitation and meanwhile acquire stable supervision signal. So that, in CSI loss, only \(U_B^T\) is learnable and all other matrices are already known. The discrimination equivalence loss for \(u_B^S\) is similar to \(h_B^S\), that is:

\[
\mathcal{L}_{de}^n = \text{CE}(y, g_B(u_B^S)) + \text{CE}(y, g^T_{Fed}(u_A^T, u_B^T)) + \text{CE}(y, g^T_{Fed}(u_A^S, u_B^S))
\]

where we use the superscript “\(n\)” (abbreviation for non-overlapped) to distinguish the same losses for the overlapped data. The losses are so-designed according to the fact that: the optimal feature \(u_B^S\) would maintain good performance in the B-side head and both the student and teacher federated classifiers. Finally, we sum up all above losses as the “A to B” transformation loss for the non-overlapped data:

\[
\mathcal{L}_{a2b}^n = \mathcal{L}_{csi}^n + \mathcal{L}_{de}^n
\]

### 3.4 Adapting Full Sample Space

After learning the cross-view partial encoder, we are do capable to make predictions in the whole sample space, however, the learnt A-side representation is not aware of the non-overlapped data distribution. Thus we design an A-side module to explicitly learn in the whole sample space and further integrate it with the federated module to make comprehensive predictions.

The A head and Federated head have complementary advantages: the former adapts well to the full-sample space (but...
partial feature space) and the latter adapts well to the full-feature space (but partial sample space). To fuse the advantages of both, we firstly let them learn mutually to enhance their own prediction, and then combine their diverse predictions as the final result. We achieve this goal via the proposed Privileged Ranking Consistency loss (PRC loss). Since the magnitudes of the predicted scores of two heads are different (due to data difference), directly forcing their values to be close may harm the prediction. Thus, we choose to maximizing their ranking consistency by using the scale-invariant pair-wise ranking information.

Inspired by the pair-wise ranking loss, we use a partial order matrix (POM) to fully describe a prediction vector’s ranking order. Each element of POM is denoted by the partial order of a sample pair. We use the probability \( p(\hat{y}_i > \hat{y}_j) \) to denote the partial order and model it with the logistic function \( \sigma(\hat{y}_i - \hat{y}_j) \). It’s obvious that, two arrangements for the same element set is identical, when and only when they hold the same partial order for any two elements. Thus we can draw closer two ranking order via drawing closer their POMs. Let’s use \( \mathbf{R} \) to denote the POM for a batch of \( N \) overlapped samples’ prediction vector \( \mathbf{y} \). Permuting the element order according to sample label, we can use three sub-matrices to denote the full POM:

\[
\mathbf{R} = \begin{bmatrix}
\mathbf{R}^{++} & \mathbf{R}^{+-} \\
\mathbf{R}^{+−} & \mathbf{R}^{−−}
\end{bmatrix}.
\]  

The superscripts “+” and “−” of the submatrix indicate the binary label value of elements, for example \( \mathbf{R}^{++} = \{ r_{ij} | i \in \mathcal{Y}^+, j \in \mathcal{Y}^− \} \). The PRC loss for the overlapped sample is defined as:

\[
\mathcal{L}^o_{prc} = \frac{||\mathbf{R}^{++} - s_g(\mathbf{R}^{++}_{Fed})||_F}{||s_g(\mathbf{R}^{++}_{Fed})||_F} + \frac{||\mathbf{R}^{−−} - s_g(\mathbf{R}^{−−}_{Fed})||_F}{||s_g(\mathbf{R}^{−−}_{Fed})||_F} - \frac{||\mathbf{R}^{+−}||_F}{||s_g(\mathbf{R}^{−−}_{Fed})||_F}  
\]

where \( s_g(\cdot) \) denotes the “\( stop \_gradient \)” operation, indicating that the gradient generated by this element will not be involved in back-propagation. The subscripts “A” and “Fed” denote which prediction head’s logit is used in the ranking matrix. The loss consists of three restriction terms imposed on three sub-matrices. For the sub-matrix generated by samples belongs to the same category (\( \mathbf{R}^{++} \) and \( \mathbf{R}^{−−} \)), we minimize the gap between the A head and the Fed head (the Fed head does not back propagate the gradient) and balance the effect of label scale. For the sub-matrix generated by cross-category comparing (\( \mathbf{R}^{+−} \)), the ground-truth value should always be 1, so we maximize its element value. For the non-overlapped data, we use \( \mathbf{V} \) to represent its order matrix, its PRC loss is similar to that of the overlapped data:

\[
\mathcal{L}^n_{prc} = \frac{||\mathbf{V}^{++}_{Fed} - s_g(\mathbf{V}^{++}_A)||_F}{||s_g(\mathbf{V}^{++}_A)||_F} + \frac{||\mathbf{V}^{−−}_{Fed} - s_g(\mathbf{V}^{−−}_A)||_F}{||s_g(\mathbf{V}^{−−}_A)||_F} - \frac{||\mathbf{V}^{+−}_{Fed}||_F}{||s_g(\mathbf{V}^{−−}_A)||_F}  
\]

Finally, we integrate the predictions from both heads using averaged logits:

\[
\hat{y} = \sigma\left(\frac{\hat{y}_A + \hat{y}_{Fed}}{2}\right)
\]
### Federated Privileged Distillation (FPD)\cite{Ren et al., 2022; Li et al., 2022a}

Two pioneer works \cite{Ren et al., 2022; Li et al., 2022a} have adopted privileged distillation to learn the student model in their methods, we consider them as possible solutions for Semi-VFL setting. While the usage of the non-overlapped data in these works are not clarified, it’s not explicitly formalized in the optimization objective. To make a fair and clarified comparison, Here we collectively call them FPD methods, and explicitly use $L_{FPD} = \beta L_{CE} + \alpha L_{CE} + (1 - \alpha) L_{KL}$ as their training objective.

Note that, the data volume of the overlapped and non-overlapped data is usually different in practise, and usually holds different distribution. These factors may largely affect the final result. To evaluate the robustness of methods over data volume, we set multiple data volume ratios in the main experiment by fixing the size of non-overlapped data and increasing the one of the overlapped data.

### Implementation Details

We use the Adam optimizer with $L_2$ regularization to avoid overfitting. The batch size is $5K$ for both the overlapped data and non-overlapped data. The validation set and test set is fixed among all cases, they both have a volume of 0.5 million. We use the validation set to conduct early stopping with 10 epochs watching. We tune hyper-parameters for all methods under the same random seed and report the best result among them. We use the same teacher models for all the methods. The learning rate and $\lambda$ are chosen following $\eta \in \{1^{-3}, 5 \times 1^{-4}\}, \lambda \in \{1^{-3}, 1^{-5}\}$, and the distillation loss weight $\alpha \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$. All experiments are conducted via an VFL simulation platform\cite{Abadi et al., 2015}.

## 4.2 Results and Analysis

The main results are shown in Figure 3. We can observe that:

- **Superiority**: JPL achieves the best performance in all cases, no matter the strengthen of the active parties’ feature sets or the data volume of overlapped size. Despite the absolute performance lift value, this do shows the strong generalizability of JPL in adapting the field partition setting and dataset size changing.
- **Adaptation of field importance**: We can observe that the

![Figure 3: Main results on two datasets. Each row reports a group of results under a certain data volume (the unit is 10 thousands). JPL robustly achieves the best performance under different data proportions and column sets. All AUC values are transformed in percentile for readability.]()
Table 2: Dataset statistics and model structure. M indicates million. "#fields" denotes the number of data fields and "#dim" denotes the total dimension of the input features after hash embedding, they are both denoted by two numbers, corresponding to the two part of attributes.

| Item          | Avazu (dim=150) | Criteo (dim=150) |
|---------------|------------------|-------------------|
| #non-overlapped| 2M               | 3M                |
| #overlapped   | 2M ~ 10M         | 1.5M ~ 7.5M       |
| #test         | 0.5M             | 0.5M              |
| positive%     | 1:5              | 1:3               |
| #fields       | 13—9             | 19—20             |
| bottom-A      | 64 → 32          | 64 → 64           |
| bottom-B      | 64 → 32          | 64 → 64           |
| top           | 32 → 16 → 1      | 64 → 32 → 1       |

column set B is more important than A, since local model trained on B achieves more than 75.5\% AUC in all cases while models trained on A never achieves that. Thus, the hardness of recovering B-side feature and the prediction quality from A-side classification head is different in two settings. Taking the experiment group of (Criteo, Dataset size=150, Column Set A) as an example, we observe that JPL achieves higher AUC improvement on the A feature sets (2.2\%) than it is in the right feature set (1.8\%) compared against FPD. Regardless of the extent of improvement from 0.1\% to 2.2\% among all results, JPL performs consistently better than baselines.

- **Adaptation of data volume**: The performance of all methods increased as the data volume arises in almost all cases. This validates the importance of data volume in affecting model performance. Besides, JPL’s superiority always holds as the data volume grows, it’s a critical point for it to use in practice.

In summary, JPL efficiently achieves the goal of Semi-VFL and consistently outperforms baseline methods.

## 5 Related Work

As one of the most noticeable task for internet companies, more and more efforts have been taken to apply federated learning in recommendation tasks [Yang et al., 2020; Liang et al., 2021; Liu et al., 2021a; Wu et al., 2022]. However, these works varies a lot in data scene (sample-wise partition or feature-wise partition) [Lin et al., 2020; Muhammad et al., 2020] and model type. Another line of work focus on improving the security 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 [Li et al., 2021b; Fu et al., 2022a; Sun et al., 2022; Yang et al., 2022]. These ideas are complementary to ours and can be combined to enhance security.

While our paper focus on improving the utility of split neural network models [Ceballos et al., 2020] in the vertical federated learning setting for advertising tasks, considering both the high inference cost problem and data restriction problem. This motivation clearly distinguish our work from many of related works. As few works with similar purposes, FedMVT [Kang et al., 2020] also uses splitNN model and consider to use all the non-overlapped data, it focuse on designing learning mechanism to complement missed data fields and labels, but do not consider the high cost of inference and not validated on recommendation tasks. [Ren et al., 2022] and [Li et al., 2022b] are pioneer works realizing the importance of inference decoupling. They “force” to transfer the knowledge of the federated model into the active party’s local model. Though the student model missed half of input fields, it do maintains noticeable performance lift over raw local models, showing the huge potential on the “information-asymmetric” distillation style. However, they only utilize the soft label as the distillation signal and do not take actions to alleviate the negative impact of field missing and sufficiently consider student’s adoption to the non-overlapped data. While we formally formalize the vertical semi-federated learning problem in this paper and provide a more comprehensive algorithm which consider both the full sample space and the full feature space. And they [Ren et al., 2022; Li et al., 2022b] can also be treated as degraded special versions of our solution.

## 6 Conclusion and Future Work

In this paper, we propose a joint privileged learning framework to achieve the goal of vertical semi-federated learning for online display advertising. We focus on the problem of field missing and data wasting. For the former, We propose learning objectives based on feature equivalence and discrimination equivalence to imitating the missed values’ functionality. For the latter, we adopt multi-head structure and transfer learning to jointly leveraging the overlapped and non-overlapped data. The proposed multi-head ranking consistency loss and ensemble loss carefully manage the consistency and diversity semantics of these two part data, leading to a better performance. Extensive experiments conducted on two widely used CTR benchmark datasets validate the effectiveness of the overall framework. Despite the focus of advertising in this paper, our methods are also suitable to other recommendation tasks. We are now testing our framework in real-world commercial advertising datasets and platforms to evaluate its effect on final profits. We also plan to further enhance its security and explore its flexibility to different kind of recommendation tasks.

## References

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