FLFE: A Communication-Efficient and Privacy-Preserving Federated Feature Engineering Framework

Pei Fang, Zhendong Cai, Hui Chen and QingJiang Shi

Abstract—Feature engineering is the process of using domain knowledge to extract features from raw data via data mining techniques and is a key step to improve the performance of machine learning algorithms. In the multi-party feature engineering scenario (features are stored in many different IoT devices), direct and unlimited multivariate feature transformations will quickly exhaust memory, power, and bandwidth of devices, not to mention the security of information threatened. Given this, we present a framework called FLFE to conduct privacy-preserving and communication-preserving multi-party feature transformations. The framework pre-learns the pattern of the feature to directly judge the usefulness of the transformation on a feature. Explored the new useful feature, the framework forsakes the encryption-based algorithm for the well-designed feature exchange mechanism, which largely decreases the communication overhead under the premise of confidentiality. We made experiments on datasets of both open-sourced and real-world thus validating the comparable effectiveness of FLFE to evaluation-based approaches, along with the far more superior efficacy.

Index Terms—federated learning, sketch, IoT, data sharing, feature engineering.

1 INTRODUCTION

Feature Engineering is a key step in data preparation for machine learning. A feature engineering process usually includes applying transformation such as arithmetic and aggregation to original features. Appropriate transformations help scale the feature and significantly improve the performance of learning models. In traditional model-evaluation-based feature engineering, data scientists first select appropriate feature combinations to generate new features through domain knowledge, and then conduct a specified machine learning model on datasets with and without the generated features to judge whether the generated features improve the model performance.

In real-world applications, we often encounter multi-party feature engineering problem, where features come from different institutions and organizations. To preserve privacy, direct feature exchange for multi-party transformation is not allowed as it leaks users’ privacy. In an example illustrated by Fig. 1 the Body Mass Index (BMI) is to be calculated form height $h$ and weight $w$ by $BMI = \frac{w}{h^2}$, while $h$ and $w$ are separately collected by two sensors $A$ and $B$. However, under the law restriction, sensors $A$ and $B$ are not allowed to exchange their data without privacy guarantee. Besides privacy, communication overhead is also a big challenge. Frequent trials to generate new features, if few of the new features are judged useful, lead to vain communication with a huge overhead.

To the best of our knowledge, there is no work in the literature that studies the secure multi-party feature engineering problem. In this paper, we present a formulation of this problem and borrow the idea of federated learning to address this problem.

Federated Learning incorporates concepts, methods, and applications on leveraging data from different parties to train a joint model without data leakage. During the training process, each participant preserves its data locally, but upload the updated weights or gradients instead. According to how data overlaps, federated learning can be categorized into horizontal federated learning, vertical federated learning and transfer federated learning [1]. Vertical federated learning is applicable to the situation where the features of participants overlap less and the sample IDs overlap more, while the horizontal federated learning is the opposite. If both features and samples overlap very little among participants, federated transfer learning can apply the models learned in the source domain to the target domain. In this paper we focus on the vertical federated feature engineering problem, in which participants share a large number of user IDs, but have disjoint user characteristics.

The primary challenge of multi-party feature engineer-
ing problem is how to preserve privacy. A straightforward and widely used method to tackle this challenge is to apply encryption methods such as homomorphic encryption (HE) and differential privacy (DP). HE encrypts the original text, and then performs various operations on the ciphertext to finally obtain the resulting ciphertext, which is expressed formally in Fig. 2. The privacy preservation performance of HE depends on the length of the secret key, but longer secret key results in not only better performance but also higher computational complexity. In terms of application, Gentry [2] proposed the first available fully homomorphic encryption algorithm by introducing bootstrapping and squashing. The disadvantages of Gentry’s HE scheme are that Bootstrapping and Squashing are extremely computationally intensive, and that as the calculation proceeds the size of the ciphertext continues to expand. Chai et al. [3] achieved a secure matrix factorization in recommendation systems through homomorphic encryption on gradient information. Different from HE, DP [4] adds noise to the data to ensure minimal data leakage. When the amount of data is small, the noise makes the final result far deviate from the accurate value. Also, a noiseless DP method was proposed in [5], but it usually requires the data to follow some certain distribution, which is difficult to satisfy in reality.

Other than the privacy issue, communication overhead of multi-party feature engineering is also a big challenge. Most of the existing feature engineering approaches make all efforts to improve the data quality and enhance the performance, but rarely consider the possible mounting communication overhead in multi-party feature engineering scenario. These methods usually adopt guided search in feature space using heuristic feature quality measures [6], [7], or perform greedy feature construction and selection based on model evaluation [8], [9]. The exhaustive and inefficient search renders the multi-party feature engineering costly in various aspects such as computing power, bandwidth and memory. For example, in the context of the Internet of Things (IoTs), the edge devices always store and transmit data that expands with increase of users, and the above feature engineering approaches will lead to a high energy consumption and place a heavy burden on the devices, especially those with small memory and low bandwidth. To this end, many works focus on lossless compression through a process of encoding and then restoration [10], [11]. However these lossless methods either do not have a straightforward mapping to federated learning, or have a training process too complicated to adopt in practice. Motivated by the limited resources of current devices, some recent works explored compression on different objects including gradients [12], [13], model broadcast [14], or local computation [15]. However usually the compression guarantees are instance specific and depend on the entropy of the underlying distribution [16]. In other words, if the data is easily compressible, then they will provably be compressed heavily, and a statistical analysis on the correlation between compression standard and training effect is required. Notably, recent works show that learning a compression scheme in a data-dependent fashion also leads to a significantly better compression ratio [17], [18]. However, it remains uncertain whether communication cost can be further reduced, and whether these methods or their combinations can achieve the optimal trade-offs between communication and accuracy of feature transmission.

To address the above two challenges, namely privacy and communication, we propose the Federated Learning Feature Engineering (FLFE), a framework to perform automated privacy-preserving and communication-efficient feature engineering. The idea behind FLFE is based on learning from labelled features besides the target dataset. At the core of the framework is a set of Multi-Layer Perceptron (MLP) classifiers, each corresponding to a specific transformation. Each classifier takes in Quantile Sketch Array (QSA) [19], a fixed-sized array formed from feature(s), and judges whether the corresponding transformation will generate a useful new feature. This procedure causes a problem in the federated setting: for a binary transformation, the two features to form a QSA may come from different participants. To this end, we present a communication mechanism among participants to keep the feature exchange confidential without the conventional encryption algorithms. The mechanism, working well with the inherent characteristics of QSA, efficiently prevent one participant’s features from leaking to the others. The main contributions of this paper are threefold.

1) We use the QSA [19] as representation of feature. QSA significantly reduces the communication overhead during multi-party feature transformations. In practice, the IoT device owners can easily adjust the length of the QSA according to the performance and operating conditions of their devices.

2) We design a unique set of feature exchange mechanism. No homomorphic encryption or differential privacy is required. It preserves privacy with very few additional operations, and is efficient in computation and communication.

3) We propose a framework which automatically performs feature engineering without model evaluation. Since less time is spent on judging the usefulness of transformations, even brutally traversing all possible combinations of features becomes feasible.

The remainder of this paper is organized as follows. Section 2 presents insight to the privacy-preserving approaches in Federated Learning and automated feature engineering. In Section 3, we define the multi-party feature engineering problem and give some necessary notations. In Section 4, we introduce some necessary components of FLFE, and then
elaborate on the workflow of FLFE. In Section 5, we conduct experiments on both open-sourced and real-world dataset. Finally we conclude the paper in Section 6.

2 RELATED WORK

In this section, we highlight the stringent privacy requirements posed by federated learning. Also, we talk about existing techniques for feature engineering and possibility to utilize them to enhance the privacy and communication effectiveness of multi-party feature engineering.

2.1 Federated Learning

Federated learning (FL) [20] is a scenario where multiple clients collaboratively train a machine learning (ML) model with the help of a central server. Each client transfers local updates to the server for immediate aggregation, without having its raw data opened to other clients. McMahan [21] first put forward the federated learning of deep networks based on iterative model averaging. Based on the split of dataset, federated learning can be categorized into vertical FL, horizontal FL, and transfer FL. In horizontal FL, the clients have different groups of data points and their features overlaps. In contrast, the clients share a joint group of data points with different features when it comes to the vertical one, of which the features become the input of deep feature transformations. In this paper, we focus on the multi-party feature engineering problem in vertical FL.

2.2 Privacy and Communication, challenges in federated learning

The main challenge is to balance the efficiency and confidentiality of communications. Most methods in federated learning encrypt data to preserve privacy, but complete encryption has a high demand for computing and communication resource. Here, we first briefly introduce the methods for privacy preservation commonly used in federated learning.

Secure Multi-Party Computation (MPC) [22] enables multiple participants to collaboratively compute a agreed-upon function with private data in a way that each party only knows its input and output (zero knowledge). The participants agree on a function to compute, and then can use an MPC protocol to jointly compute the output of that function on their secret inputs without revealing them. Secure multi-party computing can provide strong confidentiality on the premise of zero knowledge. However, for some scenarios, complex communication protocols with a significant amount of communication are required [23], [24], which renders MPC inapplicable in practical settings.

Differential Privacy (DP) is another popular tool combined with model averaging and SGD to facilitate secure FL [25]. Unlike MPC, DP ensures privacy of each individual sample in a dataset by adding noises from a specific distribution. Although DP can be efficiently implemented, it exposes plain gradients to the central server during aggregation, which is likely to be recovered. Meanwhile, the loss precision leads to an increase of communication overhead and training time. As a result, the availability of data is greatly discounted, making this technology far from the general application [26].

Homomorphic Encryption (HE) allows a certain set of computation operations (e.g., addition) to be performed directly on ciphertexts and then decrypt the results to get the true values. Though having many advantages, HE schemes also have some major limitations. The first is the restricted information space. Almost all HE schemes use integers [27], [28], so we need to convert the data to integers before encryption. Another limitation is the size of ciphertext which greatly increased after encryption. The third limitation is that more operations in encryption leads to more noise, making it harder for decryption. The last and most important is the lack of support for division operations. To sum up, current only a limited number of operations like additions and multiplications are allowed on encrypted data [29], while complex functions such as activation functions in neural networks are still not compatible with HE schemes.

The above privacy-preserving approaches sacrifice communication efficiency for privacy. In face of the mounting communication overhead, recent works on federated learning focus on compression of transmitted data. They have developed a series of technologies such as subsampling, probabilistic quantization and random mask [12], [30]. In fact, all of these technologies are looking for a universal solution for privacy preservation in federated learning. However, for some special scenarios like multi-party feature engineering, if the original data has been converted into features that can be learned by the model before training, it is likely to protect privacy without encryption. Next we list some recent feature engineering methods and analyze their applicability in federated learning.

2.3 Feature Engineering

Generalized and Heuristic-free Feature Construction [6] avoids exhaustive enumeration of feature space by the divide-and-conquer strategy and weighting-rules-based search. Markovitch et al. [7] found that the supplied set of attributes is not sufficient for creating an accurate, succinct and comprehensible representation of the target concept in classification task. In view of this, they utilized heuristically beam search and predefined a set of feature constructors to constantly transform the original features. Admittedly, the above automated feature engineering approaches do not require domain knowledge, and brutally perform more feature transformations in than manual ones in the same time. This characteristic renders them unsuitable for applications in the real world. An automated feature engineering approach in a multi-party setting should possess wisdom, that is, the ability to generate useful features with as few trials as possible. To improve the calculation efficiency, the more recent ExploreKit [9] performs automated feature engineering by combining information in original features. Meanwhile, it restricted the exponential growth of the feature space by learning both the entropy of new feature and the statistical tests on parent features. This meta-learning-based approach inspired the optimization of feature information presentation. Nargesian Konen [31] first proposed the QSA as input of meta-feature learners (models), which shows an overwhelming advantage in representation capability over manual selection of features and two-layer auto-encoder.

In summary, a viable multi-party feature engineering
framework should work automatically so that it can support more transformations in the same time. Since the effect of feature engineering depends on the distribution of data, the framework should also have access to the true distribution as much as possible under the guarantee of privacy with relatively lower communication overhead. Admittedly, some approaches in federated learning do preserve privacy, but they either require high communication overhead (MPC, HE) or sacrifice the precision of data transmission (DP). Motivated by the requirements for the above properties, we design FLFE, a federated feature learning framework that is automated, privacy-preserving and communication-efficient. The core idea of FLFE is the combination of automated feature engineering methods and a feature exchange mechanism, to which the section 4 is devoted.

3 Multi-party Feature Engineering Problem

Consider a set with $n$ devices $T = \{T_1, T_2, ..., T_n\}$. Each device $T_k$ stores a dataset $D_k$, and the feature space of $D_k$ is defined as $F_k = \{f_k1, f_k2, ..., f_km_k\}$, where $m_k$ is the number of features in $D_k$. We apply multi-party feature engineering among $\{T_1, T_2, ..., T_n\}$. According to the application conditions, multi-party feature engineering scenarios are divided into three levels:

1) there is no requirement on confidentiality or communication efficiency;
2) there is a requirement on confidentiality but no requirement on communication efficiency;
3) there is a requirement on both confidentiality and communication efficiency.

Among the three levels, the final one is the most demanding. Thus, if we can solve the multi-party feature engineering problem in the final case, then there are nothing difficult in the others.

3.1 No Requirement on Confidentiality or Communication

Suppose there is no requirement on confidentiality and communication, a simple idea is to transmit the data scattered across the devices in plain context, so that we obtain $D = D_1 \cup D_2 ... \cup D_n$. Data scientists apply appropriate transformations on features based on domain knowledge, and then use model evaluation methods such as random forest, logistic regression, etc. to verify the effect of the transformation. Except for the procedure of feature transmission, multi-party feature engineering in this scenario is nothing different from the traditional feature engineering.

3.2 A Requirement on Confidentiality, No Requirement on Communication

When there should be privacy preservation during transmission but no strict restrictions on communication overhead, the problem is amenable to encryption. Typically an encryption-based procedure conduct multi-party feature transformations as follows: Participants encrypt features with Homomorphic Encryption and transmit them to a server; The server performs transformations and decrypts the result, and the decrypted result is equivalent to the result of direct transformation without encryption; The server finally decide on whether to retain or abandon these features. Notice that a disadvantage of this procedure is that in practice, because of encryption, the transformations are limited to combinations of additions and subtractions or that of multiplications and divisions.

3.3 A Requirement on Both Confidentiality and Communication

Since the ciphertext generated by homomorphic encryption is a long byte string (usually 512 bits for one integer), transmission of the ciphertext results in a huge waste of resources, both in computation and communication. At the same time, generation of secret key during encryption is extremely time-consuming.

To further illustrate how expensive the feature engineering approaches in Section 3.1 and 3.2 are, we consider $n$ devices each with $m_k$ features, where $1 < k < n$. We need to apply a binary transformation of features from two different devices, so there are $\frac{1}{2} \times (\sum_{d=1}^{n} m_d^2 - \sum_{d=1}^{n} m_d^2)$ possible choices of the two features. Suppose $b$ binary transformations are available for selection, there are $\frac{1}{2} b \times (\sum_{d=1}^{n} m_d^2 - \sum_{d=1}^{n} m_d^2)$ possible new features. With $b$ fixed, the amount of new features and their combinations to explore grows rapidly. Hence the conventional routine of encryption, transmission, model evaluation, and then enumeration of all the transformation combinations, is not practical. A scalable method must avoid this computational bottleneck.

We design FLFE in the situation where participants share the same set of samples but with different features, which is consistent with the definition of vertical federated learning introduced in Section 1. We emphasize that FLFE aims to solve the multi-party feature engineering problems of the most difficult level.

4 The Structure of FLFE

In FLFE, our vision is to bring to light the integration of sketches and DNN to practical multi-party feature engineering problems and show a viable path towards a federated feature engineering system. As the Fig. 3 shows, the center of FLFE is a parameter server, a platform laid a set of Deep Neural Networks, with the participants in multi-party feature engineering scattered around. Communications between the device and the server, and between the device and the device are both maintained under certain bandwidth limitations. Besides the storage of DNN models, the parameter server sends instructions to coordinate feature exchange of devices and accept the sketches generated by participants. Since the multi-party feature engineering system in Section 3.2 requires participated devices to support complicated encryption-based privacy-preserving methods, here in FLFE, we assume that all the devices are at least able to perform operations with $O(n)$ time complexity.

In a nutshell, FLFE generates QSAs from features, transmit them, and feed them into a trained DNN; Then if the DNN outputs a result larger than a threshold, which means the transformation (corresponding to the DNN) works well
To calculate \( S \) label, it is transformed into a QSA:

\[
\text{class} \mid \text{with respect to this feature. To be specific, a feature corresponds to the distribution of data points in a certain bin. The output has a confidence score measuring the probability of the transformation (corresponding to the classifier) being useful on the features, the original features will be securely transmitted and transformed into a new feature. In this section, we first discuss about some essential components of FLFE, and elaborate on FLFE’s workflow in the last subsection. The components include the QSA (Section 4.1), DNNs and their training (Section 4.2), transformation judgement and feature generation (Section 4.3).

4.1 Feature Representation

In FLFE, we use the Quantile Data Sketch (QSA) [19], instead of the original features, as input of DNN classiﬁers for three reasons: (1) it does not conform to the principal of privacy preservation to transmit original features; (2) the DNN classiﬁers have a ﬁxed dimension of input, but the datasets vary in number of data points; (3) Nargesian et al. [31] found that, in terms of predictive performance, QSA is well above other representations such as Handcrafted Meta-features, Stratied Sampling, and Meta-feature Learning.

A feature (of size \( \text{num data points} \times 1 \)) is transformed into a QSA (of size \( m \times \text{num classes} \)) with the help of labels, where \( m \) is a manually set parameter. A column of a QSA corresponds to the distribution of data points in a certain class with respect to this feature. To be speciﬁc, a feature \( f \) is transformed into a QSA:

\[
R_f = [S^1_f, S^2_f, ..., S^n_f]
\]

where \( n \) is the number of classes, and \( m \) is the length of each column \( S^k_f \) (\( k = 1, \cdots, n \)).

To calculate \( S^k_f \), suppose there are \( t \) data points with label \( k \), and they are \( k_1, k_2, \cdots, k_t \), with features \( f_k \) \( \triangleq \{ f_{k_1}, f_{k_2}, ..., f_{k_t} \} \). We deﬁne \( m \) disjointed bins with size \( b_0, b_1, ..., b_{m-1} \), which are initialized to 0 and should finally satisfy \( \sum_{k=0}^{m} b_k = t \). For \( v \in \{1, 2, \cdots, t\} \), we put data point \( k_v \) in the \( id \)-th bin, as

\[
id = \left\lfloor \frac{f_{kv} - \min f_k}{\max f_k - \min f_k} \times m \right\rfloor
\]

(1)

\[
b_{id} = b_{id} + 1
\]

(2)

where \( \lfloor \cdot \rfloor \) indicates rounding down.

Notice that \( k_v \), with \( f_{kv} = \max f_k \), cannot be assigned according to the above formula, so it is directly put in \( b_{m-1} \). Repeat the above process for \( k = 1, \cdots, n \) to obtain \( R_f \). An example of QSA generation is given in Fig. 4.

Fig. 4. An example of the generation of QSA from a feature. The label is either 0, 1 or 2, so the QSA has three columns. The data points labelled as 0, 1, and 2 are correspond to the first, second, and third column separately. In this example, the number of bins is set to 2 and the actual bin index for each data point is calculated in equation (1) and (2). Generally, QSA can reveal the correlation between the distribution of a feature and the labels.

To further illustrate how a QSA is utilized by DNN Classiﬁers, Fig. 5 demonstrates the process from the generation of a QSA to the output of a classiﬁer. In order to ﬁx the input size of DNN classiﬁers for different classiﬁcation tasks, we

![Diagram of FLFE structures](Image)

Fig. 3. The overview of FLFE structures. Participants upload sketches (QSA, which will be elaborated in Section 4.1) to the server, and the server in turn issues instructions to coordinate the operation of multi-party feature engineering. DNN Classiﬁers tell whether a feature is useful from the sketches uploaded. Ideally, participants can be all kinds of communication devices that hold features.

![Diagram of QSA generation](Image)

Fig. 4. An example of the generation of QSA from a feature. The label is either 0, 1 or 2, so the QSA has three columns. The data points labelled as 0, 1, and 2 are correspond to the first, second, and third column separately. In this example, the number of bins is set to 2 and the actual bin index for each data point is calculated in equation (1) and (2). Generally, QSA can reveal the correlation between the distribution of a feature and the labels.

![Diagram of QSA utilization](Image)

Fig. 5. The process from sketching a feature to getting an output of DNN classiﬁer. A QSA is generated from a feature, scaled to \([-k, k]\) separately for each class, ﬂattened, and fed into DNN classiﬁers. The depth of color in QSA represents the number of data points put into the certain bin. The output has a conﬁdence score measuring the probability of the transformation (corresponding to the classiﬁer) being useful on the feature \( f \). In practice, we can adjust QSA parameters (number of bins and scaling range) based on the memory and bandwidth of devices.
convert the multi-class problems into one-vs-all binary classification problems. A QSA manages to convert a feature with variable length (being equal to the number of the data points) to a fixed-length array acceptable for Neural Networks. Since the true values of features are replaced by QSA, the participants can securely transmit the QSAs without encryption. Besides, since a feature might be as long as tens of thousands, the application of QSA will also reduce a large amount of communication overhead.

4.2 Model Selection and Training

On the selection of models, our insight is an integration of Deep Neural Network (DNN) and sketches. The superior predictive performance of DNN stems from extraction of high-level features of data. However, DNN is criticized for the lack of interpretability, the ability to let a layperson to understand why a DNN delivers certain results. The sketch is mainly limited in application to the areas of network measurement and databases. We find that through integration, the defects of sketches and DNN interestingly reverse to optimize two sides of the same coin (performance and privacy in multi-party feature engineering). There are two reasons: (a) First, the sketch, usually a fixed-sized array, attains high accuracy with succinct data structure, and reach an adjustable trade-off between accuracy and memory. This is important in attaining learning efficiency and prevent battery draining and overheating problems of mobile phones and other devices. (b) Second, we notice that the cooperation of DNN and sketches brings about inherent but little explored privacy benefits. A sketch compresses data length but preserves the feature of data so that it is difficult for people to extract information from a sketch, while the trained DNN can easily accomplish these tasks. Since DNN is well-known for its ‘Black Box’ characteristic, it is hard to know the basis of DNN inference.

The training of a DNN classifier requires sufficient labelled QSAs as training samples. We applied transformations only on numerical features in classification datasets, but not on discrete ones, to generate training samples (QSAs without labels). For a transformation, the training samples are labelled as positive if the transformation improves the performance of a base model on the dataset. Specifically, we decide the standard of improvement by evaluating a base model \(L\) (Random Forest, Logistic Regression, etc.) on the original feature and the constructed feature. If the constructed feature leads to a performance improvement beyond a threshold, the training sample will be labelled as positive. Because these QSAs are all from open-sourced dataset, it’s not necessary to keep them confidential, and the training of DNNs can be done in the parameter server.

As for the selection of DNN structure, we have tried many types of neural network structures, which vary in number of cores and depth of hidden layers. Our trials showed that even a simple Multi-Layer Perceptron (MLP) binary classier performs well on QSA prediction, and the training loss converges rapidly. This result again indicates QSA’s strong ability to extract features and easy-to-learn data structure. In our experiment, we used MLPs with only one hidden layer. For a QSA representation \(R_f = [S_1^f, S_2^f, ..., S_f^f]\), the probability of being useful is computed as:

\[
[p_{useful}(f), p_{useless}(f)] = \sigma_2(b^{(2)} + W^{(2)}(\sigma_1(b^{(1)} + W^{(1)}R_f)))
\]

Here \(\sigma_2\) and \(\sigma_1\) are respectively softmax and rectified linear unit (ReLU) functions \([33]\). \(W^{(1)}\) and \(W^{(2)}\) are weight matrices; \(b^{(1)}\) and \(b^{(2)}\) are bias. In the training procedure, we adopt Adam Optimizer \([34]\) and introduce both regulation and drop-out \([35]\) with 0.5 drop-out rate to prevent over-fitting.

4.3 Transformation Judgement

In this section, we elaborate on how we judge transformations and generate new features in FLFE. Only unary and binary transformations are considered as \(r\)-ray transformations \((r > 2)\) can be composed by unary and binary transformations. There are multiple \(r\)-ary transformations, each corresponding to a trained DNN. For \(r\) selected features \([f_1, f_2, ..., f_r]\) and each \(r\)-ary transformation, we input the QSA generated from \([f_1, f_2, ..., f_r]\) to the corresponding DNN and judge whether the transformation will produce a useful new feature. As is described in Section 4.2, each DNN classier outputs a real-valued conidence score, namely the probability of a transformation being useful. If the conidence score is above a given threshold, FLFE recommends the corresponding transformation to be applied on features \([f_1, f_2, ..., f_r]\). In consideration of the prediction error and risk of dimension explosion, we only recommend transformations which are very likely to be useful, and those ambiguously judged as useful (with conidence score around 0.5) will be abandoned.

4.4 FLFE Workflow

Based on the components introduced above, we now finally move on the workflow of FLFE.

Judgment of validness of feature transformation requires computation of the QSA. It is only when a feature’s QSA is judged as useful will FLFE actually generate features with the corresponding transformation. The enhanced privacy-preserving ability in the feature generation process is achieved mainly by the Parameter Server, which serves as an intermediary for information transmission. Parameter Server \([35]\) is a typical element in distributed machine learning, which is responsible for data storage from distributed working nodes, and allocation of computing resources through a central scheduling node. To enhance confidentiality during feature generation and transmission, we introduce a similar server-client structure into FLFE: the parameter server is set up for scheduling feature engineering and transformation, and the clients are the devices scattered around the server, as feature-holders. Different from distributed machine learning, the work of parameter server includes deciding on transformation types, designing the participants, coordinating information exchange, and storing the generated features. Generally, all participants in FLFE has full autonomy for the local data, and can decide when and how to join the federated feature engineering.
In FLFE, we define a loop as an attempt to validate the usefulness of a transformation on two features from different participants. The final output, a confidence score, measures whether the new generated feature is useful or not. Parties involved in a loop include a Parameter Server and at least two participants (the feature holders). The main procedure of FLFE with a parameter server and the two participants is shown in Algorithm 1 with more details elaborated in Algorithm 2 and Algorithm 3.

**Algorithm 1: The procedure of FLFE**

- **Input**: parameter server \( S_r \) that holds new features and coordinate the feature exchange, a set of participants \( dcs = \{dc_1, dc_2, ..., dc_n\} \)
- 1. \( S_r \) gets the information of \( \{dc_1, dc_2, ..., dc_n\} \);
- 2. \( S_r \) sets the \( MaxLoop \) and \( \theta \);
- 3. if \( S_r \) and \( dcs \) have prepared then
  - for loop = 1; \( loop \leq MaxLoop \); \( loop++ \) do
  - \( prob = Judge_a_QSA(S_r, dcs) \);
  - if \( prob \geq \theta \) then
    - \( Generate_a_New_Feature(S_r, dcs) \);
- 4. final;

As Algorithm 1 shows, the whole procedure of FLFE does not end until the number of completed loops reaches the \( MaxLoop \). In order to maintain the stability and efficiency of FLFE, participants in poor conditions can notify the server and then exit the loop, or the server selects the devices in good condition in priority during feature engineering. Generally, the workflow of FLFE can be described as a ‘two-step’ strategy. It is only after the first step (\( Judge_a_QSA \)) returns a confidence score higher than the given threshold \( \theta \), will a new feature genuinely be generated (the second step). Otherwise, Algorithm 1 restarts as a new loop begins.

Algorithm 2 depicts the process of judging a QSA under the coordination of the Parameter Server. Algorithm 3 demonstrates the privacy-preserving feature exchange process. It includes steps from generating a new feature among participants to sending it to the Parameter Server. Fig. 7 gives an illustration of the departure and destination of each feature transmission in the two algorithms.

In Algorithm 2, \( dc_1 \) first transmits the sketch of its feature \( f_1 \) and sends it to another device \( dc_2 \). Then \( dc_2 \) combines the received sketch with a sketch of its own feature \( f_2 \) to form a QSA. The formed QSA is sent to the Parameter Server, which then use a DNN to judge whether the formed QSA indicates a useful new feature and return the confidence score.

Algorithm 3 proceeds only if the confidence score returned by Algorithm 2 is larger than the preset threshold. To conceal true values of the feature in \( dc_1 \), we initialize a random mask vector \( f_m \), which is a vector with the same length as \( f_1 \) and \( f_2 \).

\( f_3 \) in Algorithm 3 should ideally equal to \( T(f_1, f_2) \), so

**Algorithm 2: Judge_a_QSA**

- **Input**: parameter server \( S_r \); a set of participants \( dcs = \{dc_1, dc_2, ..., dc_n\} \);
- **Output**: The probability \( \theta \) of a feature being useful;
  1. Server \( S_r \) decides on which two features, \( f_1 \) in device \( dc_1 \) and \( f_2 \) in device \( dc_2 \), are to participate in this loop;
  2. Server \( S_r \) selects a transformation \( T \) (Sum, Multiplication, etc.) and notify \( dc_1 \) and \( dc_2 \) the transformation type and \( f_1, f_2 \) separately;
  3. Device \( dc_1 \) generates sketch \( s(f_1) \) and send \( s(f_1) \) to \( dc_2 \);
  4. Device \( dc_2 \) generates sketch \( s(f_2) \), obtain the QSA \( R(f_1, f_2) \) and send \( R(f_1, f_2) \) to \( S_r \);
  5. Server \( S_r \) feeds \( R(f_1, f_2) \) into the DNN classifier corresponding to \( T \), output the probability \( \theta \) judging whether new feature \( f_3 = T(f_1, f_2) \) will be useful;
  6. Server \( S_r \) tells \( dc_1 \) and \( dc_2 \) about the judgement. If useful, both \( dc_1 \) and \( dc_2 \) prepare for the next step;
  7. return \( \theta \);

**Algorithm 3: Generate_a_New_Feature**

- **Input**: parameter server \( S_r \); a set of participants \( dcs = \{dc_1, dc_2, ..., dc_n\} \);
  1. Device \( dc_1 \) encrypts \( f_1 \) with a random mask vector \( f_m \), thus getting the encrypted feature \( f_{1e} = encrypt(f_1, f_m) \);
  2. Device \( dc_1 \) sends \( f_{1e} \) to \( dc_2 \);
  3. \( dc_2 \) calculates \( f_{3e} = T(f_{1e}, f_2) \);
  4. Device \( dc_2 \) sends \( f_{3e} \) to \( S_r \);
  5. Server \( S_r \) gets \( f_m \) from \( dc_1 \);
  6. \( S_r \) gets the final new feature \( f_3 \) by decrypting \( f_{3e} \) with \( fm \), which is expressed as \( f_3 = decrypt(f_{3e}, f_m) \);
true feature value. In face of limitless data points and feature combinations, most of which are useless, such initiatives avoid a large amount of fruitless server-participant and participant-participant communication cost. Furthermore, the Parameter Server organizes the FLFE workflow but not decides on how to encrypt and decrypt features, or the initialization of mask vector $f_m$. In FLFE, each participant keeps its local feature secret to others, and the Parameter Server only stores the generated new features. That is to say, FLFE not only reduces the communication overhead but also provides a strong privacy guarantee.

Compared with traditional feature engineering approaches, we attribute the relatively lower communication overhead to the size of QSA. Meanwhile, the privacy guarantee of FLFE is result of the joint effect of feature representation, data transmission design, and DNN’s lack of interpretability.

## 5 Experiment

We evaluate the performance of FLFE in two experiments: (1) efficacy on classification tasks compared with (1.a) instant model evaluation and (1.b) learning feature engineering (LFE) conducted separately on each device; (2) efficiency in terms of computation time and communication overhead. The former was done on open-sourced datasets, each manually split into three sub-datasets with same data points but different features, while the latter on a real-world dataset of the vertical federated learning setting.

In the first experiment, we generate all feasible combinations of features for binary transformations in advance to eliminate the error caused by random feature transformations. In other words, the three approaches always transform the same features and the difference of classification result come from the approaches themself. The second experiment doesn’t have such a setting, which means the generated new feature can be further transformed, so that the experiment can better present the actual efficiency in running time and communication overhead.

We implemented FLFE transformation classizers in Pytorch and simulate the transmission of QSA and true features in PySyft. Transformation and instant model evaluation were implemented with Scikit-learn. For FLFE, we considered the following 14 transformations: log, square-root (applied on the absolute of values), frequency (count of how often a value occurs), square, round, tanh, sigmoid, isotonic regression, zscore, normalization (scaling to $[-1, 1]$) for unary transformations, sum, subtraction, multiplication and division for binary ones.

As mentioned in section 4.2, we collected 166 open-sourced datasets from OpenML, 120 of which were used to generate QSAs as training samples and the rest were for test datasets. In these datasets, the number of features varies from 3 to 10001, and the number of data points from hundreds and tens of thousands. Random Forest and Logistic Regression (both with 10-fold cross-validation) are chosen as the test model. The performance improvement threshold $\theta$ is set to 1%. The f1-score before and after feature engineering can be calculated with the federated random forest [37]. If the f1-score shows an improvement

---

**Fig. 7. Illustration of Algorithm 3** (in this example, Addition is taken as the transformation $T$), which generates a new feature and stores it in the Parameter Server. Some details besides data transmission are elaborated: In the second picture, $dc_2$ first calculate the $f_{dc} = f_1 + f_2 + f_e$. The $f_1 + f_m$ comes from $dc_1$ and $f_2$ is stored by $dc_2$ itself. In the third picture, the server $SR$ restored the true value $f_3 = f_{dc} - f_e$. The $f_{dc}$ comes from $dc_2$ and $f_m$ is the mask vector in the first picture.

The encrypt and decrypt operations should satisfy:

$$T(f_1, f_2) = \text{decrypt}(\text{encrypt}(f_1, f_m), f_m)$$

(3)

$$= \text{decrypt}(T(f_1, f_2), f_m)$$

(4)

$$= \text{decrypt}(T(\text{encrypt}(f_1, f_m), f_2), f_m)$$

(5)

where equation (5) corresponds to the whole procedure demonstrated in Algorithm 1. The encrypt and decrypt operations vary from transformation to transformation. If binary operations are sum, subtraction, multiplication or division, and both the encrypt and decrypt operations satisfy the following equations, the target equation (5) can be met.

$$T = \text{encrypt}$$

$$f_o = \text{decrypt}(\text{encrypt}(f_o, f_m), f_m).$$

(6)

(7)

If $T$ is addition, subtraction, multiplication, or division,

$$T(T(f_1, f_2), f_m) = T(T(f_1, f_m), f_2).$$

(8)

From (6):

$$\Rightarrow \text{encrypt}(T(f_1, f_2), f_m) = T(\text{encrypt}(f_1, f_m), f_2).$$

(9)

From (7):

$$\Rightarrow T(f_1, f_2) = \text{decrypt}(T(\text{encrypt}(f_1, f_m), f_2), f_m).$$

(10)

which is exactly equation (5). Notice that unlike Homomorphic Encryption, where there is a strict requirement on the encryption, here encryption can be as simple as addition or multiplication, and the decryption is correspondingly subtraction or division.

In summary, FLFE adopts a 'two-step' strategy to address the multi-party feature engineering problems. The first step only requires the transmission of QSA instead of the...
Fig. 8. The procedure from data preparation to experiment conduction. We generate QSAs from 120 open-sourced datasets to train the DNN Classifiers. All the QSAs are labelled by a predefined base model (the labelling method is specified in Section 4.2). After training, we conduct experiments by inferring useful new features in other 46 datasets with the classifiers. Before the inference, we in advance chose a test model to compare the f1-scores before and after the experiment. Finally, we analyze the efficiency and efficacy of FLFE from the experiment results.

not less than 1% (same with the threshold θ in generation of training QSAs), the new feature will be directly appended into original dataset. The experimental procedure is shown in Fig. 8.

Two data augmentation techniques were also utilized. (1) Since higher threshold leads to training samples of higher quality but with fewer positive labels, we adopted SMOTE upsampling [38] to eliminate this imbalance. (2) Each time after labeling a feature as useful or not, we cropped the data points to generate more QSAs, as shown in Fig. 9.

Fig. 9. We cropped a feature at a random rate multiple times to generate more training samples (QSAs).

5.1 The efficacy of FLFE

We evaluate the efficacy of FLFE by comparing it to (1.a) Model Evaluation and (1.b) Learning Feature Engineering conducted separately on each device (Separated LFE). Model-Evaluation-based approaches preserve privacy through federated machine learning models such as Federated Forest [37] and Federated Logistic Regression [59]. Since we only focus on the predictive performance rather than privacy, we directly apply Random Forest and Logistic Regression as test models. In Separated LFE, each device conducts unary transformations to its own features and sends the QSAs to the parameter server.

We first chose random forest as the base model. Table 1 reports f1-scores on 11 of the 46 test datasets without feature engineering (bench score) and with feature engineering (the last 3 columns).

We then manifest the FLFE’s robustness to the choice of test model. We used random forest and logistic regression separately as test model, while fixed random forest as the base model. Fig. 10 shows the robustness of FLFE. For the 2 base models, we guaranteed that the random feature selections are the same. We generated the combinations of features for all binary transformations, and then for different base models, the same feature combinations are enumerated.

The experiments above show that the FLFE are comparable to Model-Evaluation-based approaches in f1-score, both superior to separatedly LFE. It’s also worth mentioning that under the same predictive performance, FLFE generated fewer new features than Model-Evaluation-based approaches in most cases, and thus had lower communication overhead.

Fig. 10. Number of datasets (among the 46) for which the f1-score was improved. The results show that even when the base model and the test model are inconsistent (random forest and logistic regression), FLFE can improve the f1-score. For Random Forest being the base model and test model, FLFE even improves the f1-score on more datasets than the other approaches.

5.2 The efficiency of FLFE

In this section, we evaluated the efficiency of FLFE, Homomorphic-Encryption-based LFE (HE-based LFE) and Model-Evaluation-based feature engineering in two aspects: running time and communication overhead. Experiments were done on three real-world datasets on insurance default prediction that share the same data points but with different feature domains: Public (30 features), Insured Company

1. The chosen 11 test datasets all have names on the original features, so the generated features have clear meanings.
TABLE 1
Statistics of datasets and f1-score of FLFE and other multi-party feature engineering approaches with Random Forest being the base model. The best approach for each dataset is shown in bold. The number of added features is listed in brackets. For most datasets, the performance of FLFE was comparable to that of evaluation-based approaches, but FLFE has a far lower number of generated features.

| Dataset   | Numerical Features | Bench Score | FLFE          | separated LFE          | Model Evaluation          |
|-----------|--------------------|-------------|---------------|------------------------|---------------------------|
| churn     | 16                 | 81.01%      | **81.84%(1)** | 81.68%(1)              | 81.10%(0)                 |
| boston    | 16                 | 78.04%      | 77.81%(30)    | **81.84%(1)**          | 79.72%(30)                |
| statlog   | 10                 | 78.02%      | **92.55%(17)**| 92.19%(30)             | 91.07%(568)               |
| tecator   | 124                | 91.75%      | 87.29%(10)    | 87.28%(9)              | **88.76%(11)**            |
| hmeq      | 11                 | 87.00%      | 70.94%(18)    | 70.52%(11)             | **71.76%(106)**           |
| triazines | 34                 | 66.84%      | 55.23%        | 56.35%(12)             | 56.09%(4)                 |
| wisconsin | 32                 | 90.52%      | **91.27%(3)** | 90.39%(0)              | 90.44%(146)               |
| autoPrice | 15                 | 90.52%      | **93.79%(370)| 92.91%(129)            | 93.60%(8446)              |
| clean     | 168                | 55.23%      | 56.35%(15)    | 56.09%(4)              | **77.73%(55)**            |
| heart-statlog | 10       | 77.47%      | **81.46%(15)**| 80.60%(4)              | 95.52%(1)                 |
| zernike   | 47                 | 92.81%      | 90.52%        | 95.62%(4)              | **99.80%(171)**           |

(248 features), and Government (92 features). We set up a parameter server and 3 devices, and each device keeps one of the datasets in local. Since the main goal in this section is to evaluate the efficiency of communication, we apply only binary transformations between input features from two different devices. Note that in the previous experiment in Section 5.1, we generate new features only from original features, but in this section, we generate new features also from previously generated ones. We believe that such a setting is closer to the real practical application of FLFE, and it more clearly shows the efficiency difference of different feature engineering approaches. Note that since Palliar does not support encryption for division operations, we estimated the running time and communication overhead of division with those of multiplication.

TABLE 2
Running time spent in each loop of different multi-party feature engineering approaches. Each approach makes 500 attempts to generate useful features and the average time is reported.

| Time Part | Approach | FLFE | HE-based LFE | Model Evaluation |
|-----------|----------|------|--------------|------------------|
| Judging   |          | 0.0299s | 0.0611s | 1.0708s          |
| Generating|          | 0.0114s | 2.2933s | 0.0257s          |

Running time consists of judging time and generating time. Judging time is spent on judging whether a transformation is useful, while generating time is for generation using transformations judged as useful. Table 2 shows that FLFE is far more superior to the other two methods in terms of running time. The HE-based approach is much slower in generation for two reasons: (1) It needs to generate secret and public keys in every loop; (2) Encrypting and transmitting features are extremely time-consuming. On the contrary, the bottleneck of the evaluation-based method lies in the stage of judgement, which further slows down the entire feature engineering process as the number of features increases.

Fig. 11 and Fig. 12 present us with the trend of communication overhead in multi-party feature engineering with the number of executed loops grows. Generally, the communication overhead during the execution of FLFE largely depends on the size of QSA. For instance, a QSA with 2 class labels and 200 bins requires a device to transmit 400 floats, namely 1600 Bytes in most computer systems. The overhead of HE-based approach in the judgement stage is roughly equal to that of FLFE. However, homomorphically encryption of a feature makes it longer (from 8 bits to 256 bits in the experiments) and thus needs a higher bandwidth for transmission, which makes the communication overhead of HE-based approach higher. In Fig. 12, the communication overhead of the Evaluation-based model grows much faster than the others, and this is because for the Evaluation-based model, the feature space expands substantially as new
features are added.

6 CONCLUSIONS AND FUTURE WORK

In this paper, we studied the problem of multi-party feature engineering, which poses a big challenge of privacy and communication. We proposed a framework called Federated Learning Feature Engineering (FLFE) to perform multi-party feature engineering. The proposed feature transmission mechanism and QSA are the two cores that make FLFE privacy-preserving and communicationally efficient. The feature transmission mechanism enables each device to keep its information private by using an erasable random mask vector. The QSA utilizes the characteristics of features, instead of the features themselves, and thus can hide the private information. Besides, QSA is a fixed-scaled array, substantially reduces communication overhead and enhance the privacy. In the setting of the same level of privacy, simulations showed that FLFE outperforms existing methods by a large margin in terms of communication overhead. A future direction is to develop a method that automatically adapts the QSA size according to the dataset. It would also be interesting to explore more powerful representation of features, since QSA does not incorporate some important information such as absolute values.

REFERENCES

[1] Q. Yang, Y. Liu, T. Chen, and Y. Tong, “Federated machine learning: Concept and applications,” 2019.
[2] C. Gentry and D. Boneh, “A fully homomorphic encryption scheme,” Stanford university, Stanford, 2009, vol. 20, no. 9.
[3] D. Chai, L. Wang, K. Chen, and Q. Yang, “Secure federated matrix presentation of features, since QSA does not incorporate some important information such as absolute values.

[11] B. R. Stojkoska and Z. Nikolovski, “Data compression for encryption,” 2017 25th Telecommunication Forum (TELFOR), 2017, pp. 1–4.
[12] A. Khaled and P. Richtárik, “Gradient descent with compressed iterates,” arXiv preprint arXiv:1809.04716, 2019.
[38] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, “Smote: synthetic minority over-sampling technique,” Journal of artificial intelligence research, vol. 16, pp. 321–357, 2002.

[39] S. Yang, B. Ren, X. Zhou, and L. Liu, “Parallel distributed logistic regression for vertical federated learning without third-party coordinator,” 2019.