Secure Publish-Process-Subscribe System for Dispersed Computing

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***Abstract*—Publish-subscribe protocols enable real-time multi-point-to-multi-point communications for many dispersed computing systems like Internet of Things (IoT) applications. Recent interest has focused on adding processing to such publish-subscribe protocols to enable computation over real-time streams such that the protocols can provide functionalities such as sensor fusion, compression, and other statistical analysis on raw sensor data. However, unlike pure publish-subscribe protocols, which can be easily deployed with end-to-end transport layer encryption, it is challenging to ensure security in such publish-process-subscribe protocols when the processing is carried out on an untrusted third party. In this work, we present $\mathcal{XYZ}$, a secure publish-process-subscribe system that can preserve the confidentiality of computations and support multi-publisher-multi-subscriber settings. Within $\mathcal{XYZ}$, we design two distinct schemes: the first using Yao's garbled circuits (the GC-Based Scheme) and the second using homomorphic encryption with proxy re-encryption (the Proxy-HE Scheme). We build implementations of the two schemes as an integrated publish-process-subscribe system. We evaluate our system on several functions and also demonstrate real-world applications. The evaluation shows that the GC-Based Scheme can finish most tasks two orders of magnitude times faster than the Proxy-HE Scheme while Proxy-HE can still securely complete tasks within an acceptable time for most functions but with a different security assumption and a simpler system structure.**

***Index Terms*—IoT; Security; Privacy; Secure Multi-Party Computation;**

I. Introduction

Modern interconnected networked systems like Internet of Things are dispersed often requiring a strategic, opportunistic movement of computation to data, and data to computation, in a fashion that best suits user application needs. Recent developments in IoT enable applications to use multi-point-to-multi-point communication by use of the publish-subscribe (pub-sub) paradigm [1]. The publish-subscribe messaging allows multiple data consumers to connect to streams of real-time data from multiple sensors. Commonly used examples of pub-sub protocols are Message Queue Telemetry Transport (MQTT) [2], Advanced Message Queuing Protocol (AMQP) [3] and commercial pub-sub platform as a service (PaaS) providers such as PubNub [4] with their own proprietary protocols and APIs. The key idea behind pub-sub protocols is the use of a broker as a relay, which is typically centralized on a cloud server, such as Mosquitto [5]. Sensors (also called publishers) publish messages to specified "topics" that are sent to the broker; data consumers (also called subscribers) send to the broker a subscribe request to specified topics and receive data from the broker. The broker in a traditional pub-sub system plays primarily a message-forwarding role with optional extension to client authentication, but this basic functionality does not serve the emerging need for data processing in such systems [6]. Enabling data processing on the broker before forwarding instead of merely relaying raw data helps provide more meaningful data derived from raw sensor data and detect potential anomalies. In some cases, it can also reduce the overall throughput and improve clients' energy efficiency. This is important in IoT environments considering the fact that most IoT devices are of a low-budget setting. One of the examples is that PubNub's BLOCKS [7].

However, as brokers are typically hosted on third-party servers, adding processing to pub-sub middleman introduces concerns about security. An application that wishes to make use of a third-party broker for traditional pub-sub messaging could use end-to-end encryption to provide security [8], but with computational functionality being moved to the server, such encryption is no longer enough. Additionally, approaches like moving computation to clients simply do not work when sensitive individual data has to be aggregated but protected, for example, building privacy-preserving machine learning models from sensitive data of medical sensors [9] and federally aggregating model parameters from multiple IoT users while preventing information leakage especially for users with small datasets [10]. To our knowledge, with the exception of proposals [11], [12] to utilize trusted execution environments, there is no prior practically implemented protocol that provides secure

computation on a pub-sub broker for IoT. Given the security vulnerabilities identified with SGX in recent years [13], [14], a system based on secure computation would be more desirable. Such a system has the potential to dramatically lower the barrier for use of third-party edge/cloud-based computation, especially for privacy-sensitive data streams such as data from smart homes and wearable devices collecting physiological information. As for reducing cost impact from secure computation on IoT devices, clients in our system are only required to encrypt or decrypt data. This overhead is the relatively cheap part in secure computation and has already existed in previous pub-sub messaging protocols.

Our Contributions. Our core contributions can be summarized as follows:

1) It is challenging to integrate multi-party computation into IoT messaging protocols constricted by its pub-sub structure despite the growing need of intelligent movement between secure computation and data. We build a system, $\mathcal{XYZ}$, to bridge this gap.
2) $\mathcal{XYZ}$ is a secure publish-process-subscribe system based on MQTT for IoT applications that can perform secure multi-party computation on the broker side. We propose and implement two distinct multi-party computation schemes with different system constructions and security assumptions. Our system supports multi-publisher-multi-subscriber settings.
3) The first scheme is based on Yao's garbled circuits [15]. We introduce techniques like communication reduction and seed synchronization to circumvent the constraints of traditional pub-sub. We also provide forward-secure seed for extra security.
4) The second scheme is based on homomorphic encryption [16] and proxy re-encryption [17]. We introduce techniques like key exchange reduction to mitigate conflicts between proxy re-encryption and traditional pub-sub structure, and subscriber representative mechanism to support multi subscribers.
5) We evaluated $\mathcal{XYZ}$ on different functions, i.e., mean, variance, weighted mean, private set intersection and secure federated learning. The function library in our system can be easily extended to support more complex functions. We also provide concrete real-world IoT applications based on our system.

The rest of the paper is structured as follows: in §II we provide an overview of our secure publish-process-subscribe system and its related work; in §III and §IV we introduce two different schemes (the GC-Based Scheme and the Proxy-HE Scheme) in our system respectively; in §V and §VI, we implement and evaluate our system with concrete real-world applications demonstration.

II. Overview and Related Work

A. Overview

Our secure publish-process-subscribe protocol should handle secure computation on the broker's side using encrypted data from publishers and distribute encrypted processed data to subscribers. Our protocol involves a publishers, b subscribers and third-party server(s). We assume a semi-honest adversary $\mathcal{A}$ who can corrupt a certain set of clients and the server(s). A semi-honest adversary does not deviate from the protocol but tries to learn as much information as possible. Additionally, certain collusion is restricted. Our security definition requires that $\mathcal{A}$ only learns the data from corrupted publishers and final outputs from corrupted subscribers, but nothing about honest parties' inputs.

Ideal Functionality. We describe the ideal functionality as a generic definition of a secure publish-process-subscribe protocol. Our ideal functionality $\mathcal{F}$ interacts with participating parties as shown in Figure 1.

Initialization

- Each new publisher sends a policy to the broker specifying allowed computation on its data.

Publish

- Each publisher publishes its data to $\mathcal{F}$. If the data from a publisher is not received in the given time period, $\mathcal{F}$ marks it as null.

Subscribe

- To subscribe to the computation C, each subscriber sends a subscription message to the broker containing requested C.
- The broker sends C and its subscribers to $\mathcal{F}$.

Process

- $\mathcal{F}$ determines a subset $P' \subset P$ of publishers whose data can be used for C, then sends P' to the broker.
- The broker sends back P_C whose policies allow C.
- If data of all available publishers in P_C is enough for C, $\mathcal{F}$ evaluates it and sends the result to subscribers, otherwise $\mathcal{F}$ sends an empty message to subscribers.

Fig. 1: Ideal World Functionality

Real-World Schemes. Our system adopts two different multi-party computation schemes using garbled circuits and homomorphic encryption with proxy re-encryption respectively with different security assumptions and system constructions. This availability of different designs offers users more choices to better fit specific needs when constructing secure publish-subscribe-process systems in practice. The summary of scheme comparison is listed in Table I. The two schemes have different security assumptions. The detailed definitions of $\mathcal{A}$ in our two different schemes will be described in §III and §IV. In terms of the system complexity, our GC-Based Scheme needs both the garbler and the broker on third-party servers.

Even with our reduced communication extension, which circumvents the direct communication among the garbler and clients in pub-sub setup, this scheme still requires the garbler as an independent intermediate party. Additionally, procedures like key ratcheting and seed synchronization are needed for indirect communication between clients and the garbler as well as seed sharing for multi-party support. On the contrary, the broker can act as a proxy in the Proxy-HE Scheme, which can be easily constructed on top of standard pub-sub protocols. As a trade-off, the Proxy-HE Scheme is in general slower.

Scheme	GC-Based	Proxy-HE
Adversary	can't control both Garbler and Broker	can't control both Broker and Subscribers
System Complexity	needs both Garbler/Broker	only needs Broker
Issues	seed sharing; data reusability	computation overhead
Typical Cost	~10 ms	~1000 ms
*Typical cost is from computing variance with 100 publishers.		

TABLE I: Comparison of Two Schemes in Our System

B. Related Work

Secure Pub/Sub System. Previous studies on secure pub/sub messaging systems have been conducted and secure pub/sub schemes have been proposed [18], [19], but these work all focused on the simple pub/sub system without a computation functionality from the broker.

Cryptographic Primitives & Systems. Our secure publish-process-subscribe system is related to the work on garbled circuits [20]–[23] and homomorphic encryption [24], [25]. However, existing schemes do not directly fit our real-time publish-process-subscribe system. Kamara et al. developed two protocols, a covertly secure protocol that outsources the garbled circuit generation and a maliciously secure protocol that outsources evaluation [20]. Carter et al. also proposed a maliciously secure protocol that outsources garbled circuit evaluation but uses a new oblivious transfer mechanism to reduce bandwidth and computation [21]. Bachrach et al. developed a protocol that allows a set of parties with data stored in the cloud to compute on encrypted data using a third-party evaluator [23]. All the work above attempted to provide a solution to more general cloud server models using garbled circuits but didn't address the issues from the publish-subscribe protocol's unique messaging mechanism. Different from how garbled circuits work, homomorphic encryption [16] allows arbitrary computation on encrypted data. Gentry proposed the first fully homomorphic encryption scheme [24], [25] followed by several improved schemes, e.g., the BGV scheme [26]. Dijk et al. showed that privacy-preserving outsourced computation on data from multiple parties and supplying output to multiple parties requires, in addition to homomorphic encryption, access-controlled ciphertexts and re-encryption [27]. They reduce a scheme that computes data from two parties and supplies outputs to two parties to black-box program obfuscation, which is hard to accomplish in general. Additionally, restrictions on parties in the paper make its potential application less realistic. Nikolaenko et al. proposed a scalable privacy-preserving system for ridge-regression combining additive homomorphic encryption and Yao's garbled circuits [28]. In their setting, a single evaluator is interested in learning ridge regression over data of a large number of data owners without learning the individual data of data owners. Our system works in a different way: (*a*) we don't want to reveal output to the evaluator, (*b*) we support a multi-sub-multi-pub setting with an extensible function library, and (*c*) our data owners, publishers, are oblivious of subscribers and subscribers are oblivious of publishers.

IoT with Proxy Re-Encryption. We also make use of proxy re-encryption in our Proxy-HE Scheme. This scheme, first proposed as a method to delegate decryption rights [17], solves the asynchronous encryption issue in publish-subscribe protocols where a publisher might publish its data long before a subscriber subscribes to a topic without knowing who the subscriber is but message encryption requires key exchange between these two parties as the first step. Polyakov et al. proposed a proxy re-encryption scheme based on homomorphic encryption to tackle this problem [8]. However, their work focused on the simple publish-subscribe setup and did not further address the issue that publishers and subscribers need to communicate back and forth via the broker to generate re-encryption keys every time a communication is established. Our work use their library but apply it with additional optimization.

III. The GC-Based Scheme

In this section, we describe our scheme designed with Yao's garbled circuits. The overall structure of the scheme is shown in Figure 2. In the real world, $\mathcal{F}$ is replaced by our scheme described in §III-B.

A. Components

Yao's Garbled Circuits. Yao's garbled circuits [15] allows the participating parties to evaluate their private inputs in a function even if they do not trust each other. Yao's garbled circuits GC, with algorithms $(G, Encode, Eval, D)$, can be defined as follows [29]:

1) On input circuit c, the garbling algorithm G outputs a garbled circuit C, encoding e and decoding d.
2) On inputs (e, x), the encoding algorithm $Encode$ outputs a garbled output X, where x is the original input. Then the evaluation algorithm $Eval$ takes in (C, X) and outputs a garbled result Y.
3) On inputs (d, Y), the decoding algorithm D outputs the plaintext.

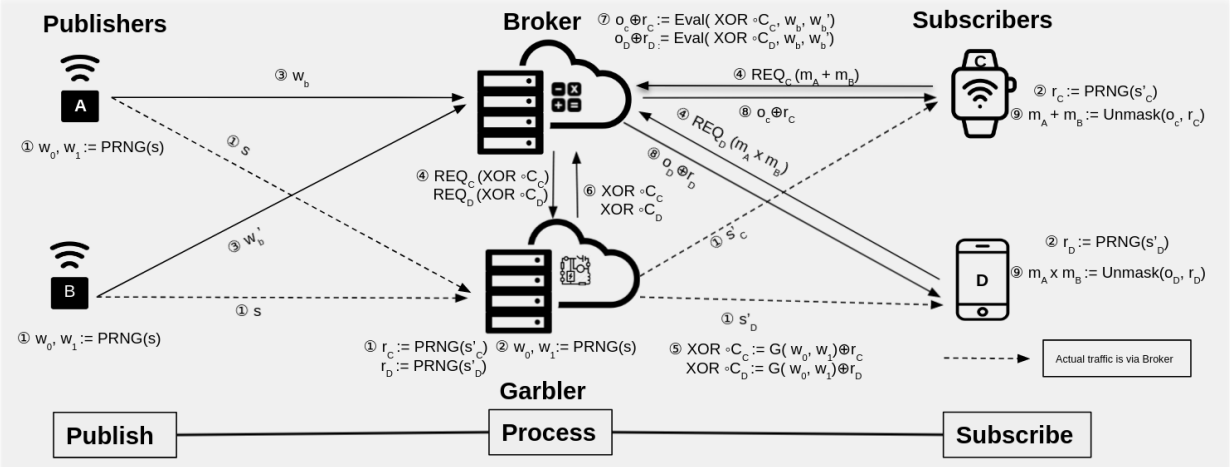


Fig. 2: Structure of the GC-Based Scheme: two cloud servers but the actual communication between clients and the garbler is via the broker

Reduced Communication Extension. The basic protocol assumes direct communication with the garbler. However, the publishers and subscribers in our system communicate with the garbler only through the broker. To address this issue, we describe an extension that allows clients and the garbler to generate wire labels/masks independently. This ensures our scheme's compatibility with a standard publish-subscribe system where all communication is only through the broker.

Publishers and the garbler share a random seed s and use a pseudorandom number generator to independently generate two wire labels for each input bit, circumventing wire label exchange between publishers and the garbler. Similarly, subscribers for the computation C and the garbler share a truly random seed s' and use a pseudorandom number generator to independently generate output masks, avoiding direct output mask exchange between subscribers and the garbler.

Seed Synchronization. The above method requires synchronization between clients and the garbler. We adapt the key ratcheting protocol of Signal, a popular secure messaging protocol, to generate seeds securely. Ratchet keys work by advancing a secret key at every round using the preimage-resistance property of a cryptographic hash function [30] [31]. At any round, a seed can be derived from a ratchet key to be used to generate pseudorandom strings. To maintain synchronization of the ratchet keys between the clients and the garbler, when sending values, publishers add the round of the ratchet key to derive the seeds used to generate the labels in the message. When the broker requests the garbling of the circuit to the garbler, it also specifies the rounds of the values it will use, such that the garbler can advance the ratchet key accordingly to derive the same seed and generate matching labels. Similarly, the garbler tells the broker the function ratchet key round for generating the mask, such that the broker can forward this information to subscribers which in turn advance their stored ratchet keys to derive a matching mask.

Forward-Secure Seeds. While the extension reduces publishers' and subscribers' communication with the garbler significantly, an adversary stealing a seed s from a publisher and colluding with the broker compromises the confidentiality of all of the publisher's inputs, including past, current, and future inputs. Similarly, an adversary stealing the seed s' for the computation C from a subscriber and colluding with the broker compromises the confidentiality of outputs of all executions.

We design an extra procedure that ensures that seeds are forward-secure, i.e., an adversary stealing a seed wouldn't be able to compromise the confidentiality of any past inputs and outputs. The key ratcheting used in our scheme can make all seeds s and s' forward-secure. An adversary stealing publishers' seed s or subscribers' seed s' would still learn all current and future inputs of the publisher or outputs for computation C. But once the adversary compromises target clients, it will learn this information anyway with or without stealing the seeds. The detailed protocol can be found in Figure 3.

B. Protocol Design

As shown in Figure 2, the design of our GC-Based Scheme includes four major parties: publisher(s), the broker, the garbler, subscriber(s). We first describe the threat model for this scheme and then explain the detailed design in two different settings: single-publisher-single-subscriber and multi-publisher-multi-subscriber.

Adversary Model. In the GC-Based Scheme, we have four parties in $GC(a, b)$: a publishers, the broker, the garbler and b subscribers as defined.

Definition 1 (The GC-Based Adversary)**.** *A semi-honest adversary $\mathcal{A}_{\mathcal{GC}}$ can corrupt any subset of b subscribers and at most $a-2$ publishers. $\mathcal{A}_{\mathcal{GC}}$ can corrupt the broker or the garbler, but not at the same time. In other words, the broker and the garbler can not collude.*

Single-Publisher-Single-Subscriber. To publish a value, the publisher generates two wire labels w_0 and w_1 for

every bit b of the value, sends both labels w_0 and w_1 to the garbler, and only w_b to the broker; the broker receives the computation request from the subscriber and requests the garbler to garble the circuit; the garbler sends the masked result back to the broker for it to evaluate; the subscriber unmasks the result from the broker.

Multi-Publisher-Multi-Subscriber. The multi-sub functionality can be realized by the garbler specifying a same rachet key round number to share the same mask seed with subscribers of the same computation. Similarly, the multi-publisher functionality in the GC-Based Scheme requires that publishers to also have a synchronized seed for a same set of labels for the same computation. This synchronization is hard to realize upon publishers' publishing encrypted data. A work-around would be the garbler translating labels into one uniform set and informing the broker to do the same encrypted translation for wire labels it received from different publishers.

Figure 3 depicts how our GC-Based Scheme works and the security analysis can be found in Appendix A. .

IV. The Proxy-HE Scheme

In the previous section, we construct a secure publish-process-subscriber scheme using Yao's garbled circuits, which requires both the broker and the garbler. Additionally, our GC-Based Scheme restricts the adversary to compromising only one third-party server (the broker or the garbler) at one time while also requiring communication between the garbler and clients goes through the broker. However, in the IoT setting where typically IoT broker services are operated by one single commercial entity, it is difficult to set up two non-colluding servers.

In this section, we design a Proxy Homomorphic Encryption (Proxy-HE) Scheme with a simpler structure and a different security assumption while addressing the issues discussed above. It also uses proxy re-encryption to solve encryption issues in secure publish-subscribe systems. The system structure is shown in Figure 4. In the real world, $\mathcal{F}$ is replaced by our scheme.

A. Components

Homomorphic Encryption. Homomorphic encryption (HE) [16] is a scheme that allows computation to be performed on encrypted data without revealing the data to the computing parties. HE in general, with algorithms $(G, Enc, Eval, D)$, can be defined as follows:

1) Key Generation Algorithm G outputs a key pair (Pk, Sk). Encryption Algorithm Enc takes in messages $m_1, \cdots, m_n$ and Pk, then outputs $C_1, \cdots, C_n$.
2) On inputs $(C_1, \cdots, C_n)$ and the computation f, Evaluation Algorithm $Eval$ outputs the result C_{result}.
3) Decryption Algorithm D takes inputs (Sk, C_{result}) and outputs the plaintext result $f(m_1, \cdots, m_n)$.

Proxy Re-Encryption. Proxy re-encryption (PRE) delegates decryption rights [32] that enables ciphertexts

Initialization

- Each new publisher sends the broker a policy specifying allowed computations on its data.
- Each new publisher generates and sends to the garbler a random seed s, which will be used to create wire labels without interaction.

Subscribe

- To subscribe computation C, each subscriber sends a subscription request to the broker. If the broker does not allow a subscriber to learn C's output, it sends back an error message.
- Each new subscriber shares a truly random seed s' with the garbler for masking/unmasking the result.

Publish

- To publish kth value, the publisher generates two pseudorandom wire labels, w_0 and w_1, using a seed s from a pseudorandom number generator (PRNG), for each bit of the value. w_0 is ith and w_1 is $(i+1)$th numbers in pseudorandom sequence generated using s, where $2kL \leq i < 2(k+1)L$ with L being the bit-length of a value.
- For input bit b, the publisher sends wire label w_b to the broker.

Process

- After receiving w_b, the broker sends the garbler identifiers of publishers along with the set of subscribers allowed to the computation, then requests the garbler to garble circuit for $XOR \circ C$. XOR is used to mask the output of the circuit.
- The garbler independently generates input wire labels using s from each publisher and an output mask r using s' for the output.
- The garbler generates a garbled circuit GC for the circuit $XOR \circ C$ using both wire labels for each input bit, w_0 and w_1 for a bit b. The garbler uses the mask r it to mask the output o of C, such that evaluating GC would result in a masked output $o \oplus r$.
- The broker evaluates the garbled circuit using wire labels sent by publishers in set P_C, obtains masked output $o \oplus r$, and sends $o \oplus r$ to all subscribers of computation C.
- Subscribers in the set S_C use r to unmask o.

Forward-Secure Seeds

- Generate a truly random key K_0.
- Generate, using pseudorandom function (PRF) with K_0, a pseudorandom seed s_0 and a pseudorandom key for ratchet Round 1. s_0 is used for pseudorandom strings during ratchet Round 0.
- At round i, using PRF with key K_i, generate a pseudorandom seed s_i and key for ratchet round $i+1$. Seed s_i is used to generate pseudorandom strings during ratchet round i.

Fig. 3: The GC-Based Scheme

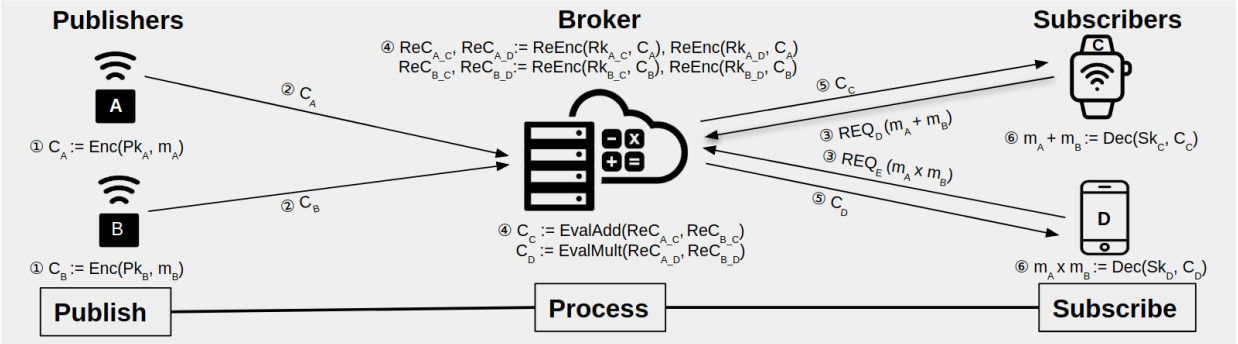


Fig. 4: Structure of the Proxy-HE Scheme: only one cloud server which handles both communication and computation

to be decrypted by a secret key that is not paired with the original public key. PRE, with algorithms (KG, E, RG, RE, D), can be defined as follows:

1) The standard key generation algorithm KG outputs a key pair (Pk_A, Sk_A) for Party A and another key pair (Pk_B, Sk_B) for Party B. Party A uses Pk_A to encrypt the message m with the encryption algorithm E, which outputs ciphertext C_A.
2) The re-encryption key generation algorithm RG takes the inputs (Pk_A, Sk_A, Pk_B, Sk_B) and outputs a key $Rk_{A\to B}$ for re-encryption. On inputs $(Rk_{A\to B}, C_A)$, the proxy then applies the re-encryption algorithm RE and outputs $C_{A\to B}$.
3) Party B applies the decryption algorithm D on inputs $(C_{A\to B}, Sk_B)$ and get the output m.

In our scheme, publishers can encrypt the data using their own public key; after proxy re-encryption, subscribers are able to decrypt the ciphertext with subscribers' secret key. This solves the asynchronization issue under the traditional publish-subscribe encryption, allowing publishers to publish messages without the need to wait for subscribers' public keys to encrypt their data.

Key Exchange Reduction. Proxy re-encryption would require that, once a subscriber requests computation, publishers (also the key authority of themselves) involved in the computation have to receive the public key from the subscriber and then regenerate a re-encryption key for re-encrypting the original encrypted data [33]. This introduces the asynchronous communication issue again under the IoT context and also an additional communication cost. To solve this problem, we design key exchange reduction. At the initialization state, the broker asks all subscribers to upload their public keys. Then each publisher regenerates a re-encryption key for each subscriber once they receive subscribers' public keys from the broker. The broker maintains a map between a re-encryption key and its subscriber-publisher pair. Every time when a new client joins the system, the broker updates the map. Under this design, whenever a subscriber requests computation, the broker only needs to find the re-encryption keys from the map to re-encrypt the data without going back to the publishers, which reduces the key exchange communication.

B. Scheme Design

Figure 4 depicts the structure of the Proxy-HE Scheme, which does not need an extra party (a garbler).

Adversary Model. The Proxy-HE Scheme $PHE(a, b)$ has a publishers, the broker and b subscribers.

Definition 2 (The Proxy-HE Adversary)**.** *A semi-honest adversary $\mathcal{A}_{\mathcal{PHE}}$ can corrupt both the broker and at most $a-1$ publishers, or, $\mathcal{A}_{\mathcal{PHE}}$ can corrupt any subset of b subscribers and at most $a-2$ publishers. It cannot corrupt the broker and subscribers at the same time.*

We believe the assumption that the broker can not collude with subscribers is acceptable because it is inevitable that the adversary can obtain a publisher's raw data when it controls both the server and subscribers.

Single-Publisher-Single-Subscriber. First, the publisher publishes encrypted data; the broker re-encrypts the data using the re-encryption key, and performs computation; the subscriber requests computation then decrypts results from the broker using its own private key.

Multi-Publisher. To operate homomorphic encryption, it is important to have data from all different publishers encrypted under the same key setting. Luckily, it is viable to handle this issue using proxy re-encryption. Once the encrypted data is re-encrypted, the data from different publishers can be considered as encrypted under the same key setting even with different re-encryption keys.

Multi-Subscriber. When a group of subscribers request the same computation, it is wasteful to recompute the result for each subscriber. It is straightforward that we can reduce the cost by only computing the result once then distributing it to all subscribers having the same request. However, it would be challenging to do so under the scheme of homomorphic encryption since each subscriber has its own key pair. We noticed that this problem is similar to the asynchronization problem between publishers and subscribers but now among subscribers. Hence, we apply PRE (2 hops) and a key map between subscribers to circumvent repetitive computation. The

Initialization

- Each client generates its own pair of public and private keys.
- Each publisher generates a re-encryption key Pk_{rp} associated with each subscriber and the broker updates the key map.
- Each subscriber is assigned with a ID number. Each subscriber works with the broker to generate re-encryption keys for others subscribers whose ID numbers are larger than its.

Publish

- Each publisher encrypts its data M using its own public key and sends its encrypted data along with a policy specifying allowed computations on its encrypted data to the broker.

Subscribe

- To subscribe computation C, each subscriber sends a subscription request to the broker and its public key Pk_s. If the broker does not allow a subscriber to learn C's output, it rejects the request.

Process

- **First Re-Encryption** Once the broker approves subscribers' request, it selects the representative subscriber X with the smallest ID in a group of subscribers requesting the same C. Then the broker reencrypts M using Pk_{rp} associated with X.
- The broker performs requested C on re-encrypted data.
- **Second Re-Encryption** The broker re-encrypts the message using Pk_{rs} for each pair of X and one of other subscribers.
- The broker sends the result of HE operations to subscribers.

Decryption

- Each subscriber decrypts the message with its own private key.

Fig. 5: The Proxy-HE Scheme

system selects the subscriber with the smallest ID as the subscriber representative, and the broker performs the encrypted computation based on this representative's key pair. Before distributing the computation result, the broker re-encrypts the result for each subscriber using the re-encryption key associated with the representative and the subscriber. Each subscriber then decrypts it using its own private key to get the result. The performance improvement using our 2-hop-PRE subscriber representative design compared to repetitive mode (repeating evaluation for each subscriber) can be found in §VI.

Our final scheme can be found in Figure 5 and the security analysis can be found in Appendix B.

V. System

$\mathcal{XYZ}$ is designed to work on top of the standard pub-sub protocols, such as MQTT. In this section, we discuss the general system design around MQTT and explain the different setups for two schemes respectively.

A. General Design

System Implementation Around MQTT. MQTT allows subscribers and publishers to indirectly communicate with each other via the broker by publishers publishing data to topics and subscribers receiving it from topics after subscribing to them. To integrate our schemes into the MQTT protocol, we require each client (either publisher or subscriber) to have a device-specific topic that allows a two-way authenticated communication between each client and the broker. The broker (and the garbler in the GC-Based Scheme) will handle the computation and distribute data. We implement the broker using Eclipse Mosquitto 1.4.15 [5] and clients using Eclipse Paho 1.3 in Python [34]. Both of them support versions 5.0, 3.1.1, and 3.1 of MQTT. We implement the cryptographic components, namely garbled circuits, homomorphic encryption and proxy re-encryption in C/C++. In our system, the Mosquitto broker has to be configured using access control list file such that certain topics where publishers publish unprocessed data are inaccessible to other clients to protect private inputs from publishers and only authorized subscribers can have access to certain computation topics.

Supported Functions. We implement five functions in our system: mean, variance, weighted mean, private set intersection (PSI) and secure federated learning (SFL). We will explain the details later in this section.

B. The GC-Based Scheme

Ratchet Keys. In the GC-Based Scheme, to improve synchronization and security of seeds, we adapt the key ratcheting protocol which can advance a secret key at every round and then deriving a seed from a ratchet key to generate pseudorandom strings. To set up the ratchet keys, the broker will forward the messages to the garbler such that clients can establish a ratchet key with the garbler. This design choice of relaying messages to the garbler through the broker is important to maintain the MQTT semantics. However, we need to add authentication in the MQTT messages using digital signatures and a key exchange protocol. This way, the secrets can be shared between the clients and the garbler via the broker. For publishers, this authenticated key exchange is used to derive the publisher's ratchet key. For every computation subscription from subscribers, key exchange is performed to derive a key to encrypt the function ratchet key from the garbler.

Extending Libgarble. Libgarble [35] is a garbling library written in C. As Libgarble is currently in develop-

ment, it lacks some functionality which we have to add in order to build and garble circuits. On the garbling side, we implement the NOT gate (expressed as the XOR of the input with 1 to take advantage of the free-XOR optimization) and the OR gate. We add arithmetic blocks to be used when building circuits in order to allow signed fixed-point multiplication and signed fixed-point division. Based on these implementations, we can build mean, variance and weighted mean.

C. The Proxy-HE Scheme

PALISADE Setup. We use PALISADE v1.10.5 [33] for the Proxy-HE Scheme. PALISADE currently provides three different homomorphic schemes, namely BGV, BFV and CKKS [36]. BGV is believed to have better performance than BFV does [36]. Thus, here we choose BGV for integer operation and CKKS for real number operation. Note that PALISADE also has built-in multi-hop proxy re-encryption. In our evaluation, we slightly modified the default scheme parameters from PALISADE for benchmark purposes. The parameter configuration can be found in Table II.

Scheme	BGV	CKKS
ring dimension	8192	8192
security level	HEStd_128_classic	HEStd_128_classic
multi depth	4	3
sigma	3.2	\
plaintext modulus	65537	\
scale factor bits	\	50
batch size	\	8

TABLE II: Scheme Parameter Configuration: to fairly compare BGV with CKKS, we try to keep ring dimensions and CRT moduli the same; we choose the base 128-bit security in our evaluation; we also select the minimum viable values of multi depth for maximum possible multiplicative depth in our evaluation.

Extending PALISADE. The current PALISADE library provides basic functions like addition and multiplication. To better fit our needs, we extend PALISADE to have functions desired in our system as discussed. More functions can be included in our system in the future. We describe our implementation of the functions under the Proxy-HE scheme as follows:

- **Mean** In our implementation, we choose between BGV and CKKS for mean. It is straightforward to implement mean on CKKS. However, BGV can only perform secure integer operations such that we cannot calculate mean by multiplying the sum and the inverse of n (a real number). This means the computation of mean on BGV requires the plaintext of n. Thus, a mean implementation on BGV will leak the number of publishers involved in the computation. If this number is not sensitive, we can choose BGV as well.
- **Variance and weighted mean** Implementing variance and weighted mean on BGV shares a similar averaging structure as mean. Thus, the scheme selection for these two functions is the same as above.
- **Private set intersection** We use Chen's algorithm [37] to construct our PSI (shown in Appendix C). We currently consider BGV for PSI since CKKS's approximation property will introduce errors with zero.
- **Secure federated learning** SFL helps securely aggregate model parameters for federated learning. We use a similar secure FedAvg structure from [10] in our current system with CKKS.

Data Transfer. We serialize cryptocontexts, keys and encrypted data into binary files for data transferring. During the initialization, we create and store cryptocontexts and corresponding keys on each machine. Then MQTT transfers encrypted data in binary. The sizes of binary files are usually 100 kb to 200 kb.

VI. Evaluation

A. Setup

We have evaluated $\mathcal{XYZ}$ on an IoT testbed with 1200 embedded computing nodes. Publishers and subscribers are run on IoT nodes (Ubuntu 18.04.5 LTS with Dual-core Intel® Atom™ E3826 and 2 GB of RAM); the broker/garbler is run on a machine (Ubuntu 18.04.5 LTS with Intel Core i7-7700 CPU and 16 GB of RAM) with sufficient computing power. Note that for some functions we run multiple processes on one node to imitate more clients.

We have selected five functions of varying complexity to evaluate the cost of the different schemes discussed above. We evaluate these functions upon receiving the values (real number for garbled circuits and CKKS; integer for BGV) from a variable number of publishers and sending results to multiple subscribers.

We put the cost into two categories: time cost for the actual computation and communication cost for the data transferred between clients and the broker as in the size of data. Our measured time includes the time of publishers encrypting data, the time of the broker evaluating data (also the time used for garbling in the GC-Based Scheme and the time used for re-encrypting data in Proxy-HE) and the time of the subscriber decrypting results. We use the data exchanged to show communication costs.

B. Results

In this part, we focus on evaluating our system regarding its multi-publisher-multi-subscriber functionality as well as its performance using different schemes.

Figure 6 shows the costs for the most relevant steps of three numerical operations involving a varying number of publishers with one subscriber requesting the computation. From our results, the GC-Based scheme has a huge advantage in both time cost and communication cost as the number of publishers increases while the difference is not noticeable for a small set of publishers.

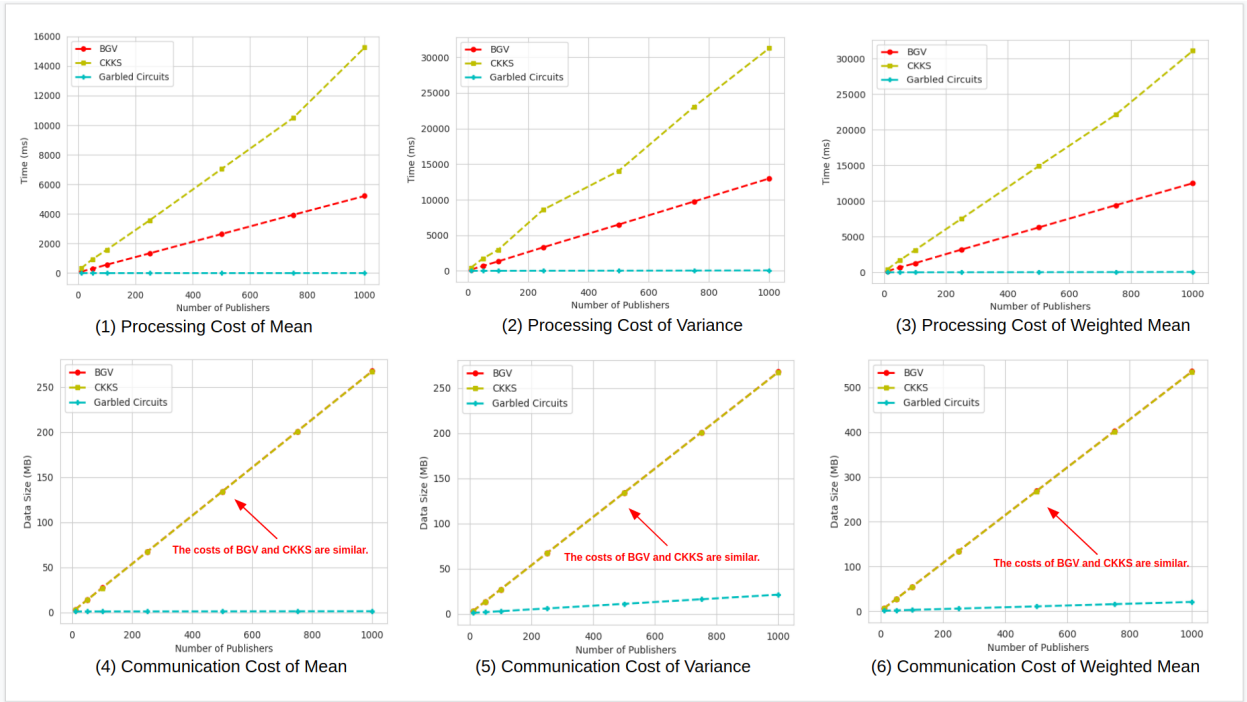


Fig. 6: Microbenchmark Results: here we have the cost on the server of three basic statistical operations (mean, variance and weighted mean).

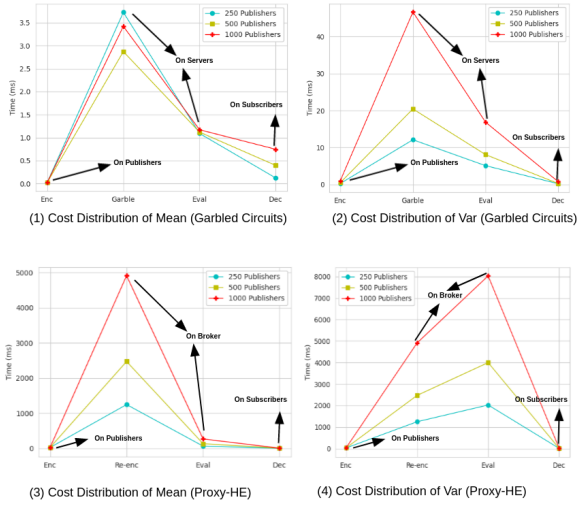
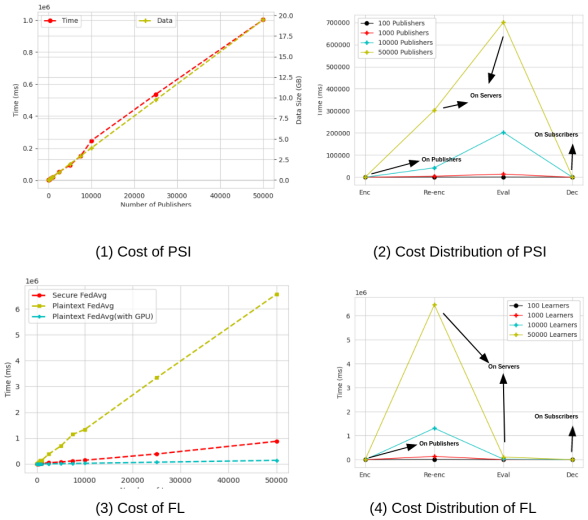


Fig. 7: Distribution of Costs for Each Step

This is because the most expensive steps of our GC-Based Scheme are the garbling and evaluation (shown in Figure 7), which do not change much for multiple publishers. Using the current version of PALISADE, CKKS nearly doubles the time cost of BGV, but the communication costs are close.

To microbenchmark our multi-subscriber functionality, we first test our system on mean function for all three implementations and also demonstrate the cost improvement in the Proxy-HE Scheme with our 2-hop-PRE subscriber representative design. We here only compare the computation cost since the communication cost between the broker and the subscribers has a nearly linear relationship with the number of subscribers. As shown in Figure 9, under our GC design, the number of subscribers should not affect the time cost in the view of the system. For Proxy-HE, our scheme introduces the cost of additional re-encryption while reducing the cost from repetitive evaluation. Figure 9 also shows that our 2-hop-PRE subscriber representative design considerably improves the performance by avoiding repetitive evaluation operation for each subscriber (re-encryption is always a lighter operation for complex functions like PSI). A further improvement could be distributing the re-encryption overload on the broker side to be parallel re-encrypting the message on subscribers instead of the broker doing all the re-encryption (around 20 ms for each subscriber on BGV and around 90 ms on CKKS but around 102 seconds for the broker with 1000 subscribers). However, this would require each subscriber to maintain a PRE key map, gets the ID of the representative and perform the re-encryption, which adds workload on subscribers.

Figure 8 depicts the performance of PSI and SFL. At the moment we implement PSI on BGV implementation. Each publisher has an array with 10 elements. During the evaluation of PSI, the first publisher's data will be computed with the rest of the publishers' data iteratively. The cost of PSI in our BGV implementation is nearly linear against the number of publishers for both types of costs. We test our SFL on CKKS on a medium-size convolutional neural network with 10 million parameters. We compare the cost of SFL in our system



(1) Cost of PSI

(2) Cost Distribution of PSI

(3) Cost of FL

(4) Cost Distribution of FL

Fig. 8: Microbenchmarks of PSI (BGV) and FL (CKKS)

Encrypt	Evaluate	Decrypt	Data
26.537 ms	24.361 ms	106.101 ms	1.196 MB

TABLE III: Cost of Contact Tracing in Our System.

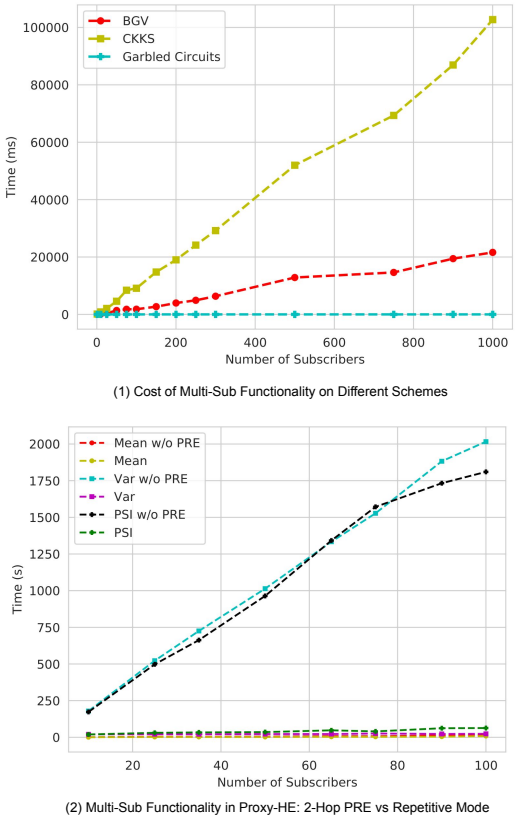
to the cost of plaintext FedAvg (GPU comparison runs on Google Compute Engine backend). The major performance drawback of our sFL is the re-encryption step because of input data size. Additionally, our SFL can be seen as an encrypted form of the regular FedAvg with acceptable approximation loss, thus the performance of our model is similar to plaintext-trained models.

C. Applications

We prepare concrete applications for IoT scenarios to show potential practical use of our system. For demonstration purposes, we use Proxy-HE Scheme here.

Contact Tracing. During the global pandemic, contact tracing becomes a promising tool to help identify the potential patients who might have contact with confirmed Covid-19 patients and slow down the spread of the virus. However, privacy is a major concern since the computation of regular contact tracing can reveal sensitive personal location data. We demonstrate a simple application using our system that implements PSI for contact tracing without the need for plaintext location information. Due to the sensitivity of the subject and the lack of available public datasets, we wrote a python program to generate random personal location datasets for testing purposes. Each person in the dataset has 10 visited locations in the same hour (in real cases the time granularity can be set to be more accurate).

In this application, we have two publishers (the confirmed patient and the potential contact) with IoT devices recording their location data. These IoT devices, for example, can be smartwatches and smartphones. The broker can be public health authorities providing service. The broker receives the encrypted location data from publishers, performs PSI on the data and returns



(1) Cost of Multi-Sub Functionality on Different Schemes

(2) Multi-Sub Functionality in Proxy-HE: 2-Hop PRE vs Repetitive Mode

Fig. 9: Microbenchmarks of Multi-Subscriber Functionality: (1) cost comparison between different schemes demonstrated using mean function; (2) performance improvement with 2-hop-PRE subscriber representative design compared to repetitive mode demonstrated using BGV.

Statistics	BGV	CKKS	BGV	CKKS
Mean	47.0 ms	173.6 ms	115.1 MB	77.2 MB
Variance	2543.7 ms	4485.8 ms	115.2 MB	77.2 MB

TABLE IV: Cost Required to Evaluate Different Statistical Measures of the Parking Lot Dataset.

whether two publishers have been in contact with each other. In Table III, the cost of PSI requires adequate computational resources on authority servers.

Daily Statistics of Parking Lots. In this application, we are interested in obtaining daily statistics of the parking lots without revealing private data at fine time granularity. For this scenario, we have one publisher for one lot, which will be sending the current number of free and occupied spots. We use the live status of the parking lots of a major airport [38] as our dataset. In particular, the airport provides updates of the number of occupied and free parking spaces for each one of the 9 parking lots every 5 minutes. This makes a total of 288 published values per day per parking lot.

We simulate the scenario by running it 288 times. The broker will accumulate the data from each day and compute the daily mean and variance for each day. From these statistics, we can have an understanding of the parking lot's operation state from a daily perspective

without invading detailed data. The cost for such an application is shown in Table IV.

VII. Conclusion

We present $\mathcal{XYZ}$, a secure publish-process-subscribe system with two multi-party computation schemes, i.e., the GC-Based Scheme and the Proxy-HE Scheme with different security assumptions and system constructions. To properly fit constraints from the traditional publish-subscribe structure, we also propose optimizations such as reduced communication extension and seed synchronization in the GC-Based Scheme and key exchange reduction along with multi-subscriber support in the Proxy-HE Scheme. Without the need for two third-party servers, our Proxy-HE Scheme has less system complexity than the GC-Based Scheme does, but yields larger overhead due to the time-consuming homomorphic encryption. Additionally, our system supports multiple publishers and multiple subscribers as well as provides an extensible library of several functions.

Our secure publish-process-subscribe system starts the conversation on integrating secure computation into IoT systems, but future work needs to be further considered such as adding support for a distributed set of brokers.

Appendix

A. Security Analysis for The Garbled Circuits Scheme

Definition 3 (UC-Security-GC)**.** *Our protocol π_{GC} securely realizes $\mathcal{F}$ in the presence of $\mathcal{A}_{\mathcal{GC}}$ in the real world, if there exists a simulator $\mathcal{S}$ in the ideal world such that for all inputs, probability distributions of the ideal world and the real world are indistinguishable.*

We describe a simulator $\mathcal{S}$ that simulates the view of the adversary $\mathcal{A}_{GC}$ in the ideal world to prove that our scheme guarantees both correctness and security.

$\mathcal{S}$ receives from $\mathcal{F}$ the number of publishers $|P_C|$ whose policy allows computing C on their data. $\mathcal{S}$ creates $2l|P_C|$ number of random wire labels $(r_0^0, r_0^1), \ldots, (r_{2l|P_C|-1}^0, r_{2l|P_C|-1}^1)$, where l being the bit-length of publisher inputs. We use a blackbox garbled circuit simulator from the projective prv.sim secure garbling scheme with circuit $M \circ C$ being the side information [39].

$\mathcal{S}$ receives $\mathcal{F}(M \circ C, \vec{x}_C)$ from $\mathcal{F}$, where M is an XOR masking function. $\mathcal{S}$ sends $\mathcal{F}(M \circ C, \vec{x}_C)$ to the garbled circuit simulator and obtains a fake garbled GC_{fake}. $\mathcal{S}$ generates a random string o_r of the same length as output. $\mathcal{S}$ sends $(GC_{fake}, r_0^0, \ldots, r_{2l|P_C|-1}^0, o_r)$ to the adversary. As garbled circuits distribution is independent of the input wire labels, GC_{fake} is computationally indistinguishable from the GC in the real execution. The random output o_r in ideal execution is indistinguishable from $o + r$ in the real execution.

In the ideal world, $\mathcal{S}$ creates a fake garbled circuit. This fake garbled circuit doesn't use wire labels $(r_0^0, r_0^1), \ldots, (r_{2l|P_C|-1}^0, r_{2l|P_C|-1}^1)$ for garbling. Otherwise, the adversary could use $r_0^0, \ldots, r_{2l|P_C|-1}^0$ labels to evaluate the circuit on $0^{l|P_C|}$, which would allow it to distinguish between real and ideal executions.

The view of $\mathcal{S}$ in the ideal world is indistinguishable from the view that $\mathcal{A}_{\mathcal{GC}}$ has in the real world execution.

B. Security Analysis for The Proxy-HE Scheme

Definition 4 (UC-Security-PHE)**.** *Our protocol π_{PHE} securely realizes $\mathcal{F}$ in the presence of $\mathcal{A}_{\mathcal{PHE}}$ in the real world, if there exists a simulator $\mathcal{S}$ in the ideal world such that for all inputs, probability distributions of the ideal world and the real world are indistinguishable.*

Our scheme guarantees both correctness and security.

Correctness. The correctness of our scheme is built on the correctness of HE and PRE [8], [25]. Our scheme $PHE = (KG, RG, Enc, RE, Eval, Dec)$ can be proven correct: for all $(Pk, Sk) \leftarrow KG(1^\lambda)$ with the security parameter 1^λ, $Rk \leftarrow RG(Pk_B, Sk_A)$, all functions f and messages m in the message space M,

$$Pr[Dec(Sk_s, RE(Rek_s, Eval(f, RE(Rek_1,$$

$$Enc(Pk_1, m_1)), \cdots, RE(Rek_n, Enc(Pk_n, m_n)))))$$

$$= f(m_1, \cdots, m_n)] = 1.$$

Privacy. As mentioned before, we do not consider the collusion adversary scenario where the compromised broker is able to collude with subscribers. Specifically, we assume the compromised broker has no access to any subscriber's secret key. We describe a simulator $\mathcal{S}$ that simulates the view of the adversary $\mathcal{A}_{\mathcal{PHE}}$.

In the real world, when $\mathcal{A}_{\mathcal{PHE}}$ compromises both the broker and a subset of publishers and subscribers, the bound of the number of publishers allowed to be compromised is $a-1$. This means that if there is only one honest publisher and the rest are all controlled by $\mathcal{A}_{\mathcal{PHE}}$, that honest publisher's input is unknown to $\mathcal{A}_{\mathcal{PHE}}$ due to the fact $\mathcal{A}_{\mathcal{PHE}}$ does not have access to any private key that can decrypt the data. In the case where $\mathcal{A}_{\mathcal{PHE}}$ compromises both any subset of the subscribers and a subset of publishers, the bound of the number is $a-2$. $\mathcal{A}_{\mathcal{PHE}}$ has the final plaintext output of the computation and the rest of $a-2$ publishers' inputs but is unable to infer the values of the 2 honest publishers' inputs. In the ideal world, $\mathcal{S}$ submits compromised publishers' inputs but learns nothing about the honest publishers' inputs. $\mathcal{S}$'s view in the ideal world is indistinguishable from $\mathcal{A}_{\mathcal{PHE}}$'s view in the real world.

C. Implementation of Private Set Intersection on BGV

This appendix shows the PSI algorithm we use in BGV.

Algorithm 1: Private Set Intersection

Input: Two lists of items A and B
Output: Indices of intersection items
initialization;
$Encrypt(A)$;
$Encrypt(B)$;
while $i < len(B)$ **do**
  sample a random non-zero plaintext element r_i;
  $temp1 = EvalSub(B_i, A_0)$;
  $temp2 = EvalSub(B_i, A_1)$;
  $C_i = EvalMult(temp1, temp2)$;
  while $j < len(A)$ **do**
    $C_i = EvalMult(C_i, EvalSub(B_i, A_j))$;
    j++;
  end
  $C_i = EvalMult(r_i, C_i)$;
  i++;
end
$Decrypt(C)$;
while $i < len(C)$ **do**
  $Compare(C_i, 0)$;
end

Algorithm 2: Secure FedAvg

Input: A list of model parameters from n learners P and a scailingfactor array s
Output: Aggregated model parameters C
initialization;
$Encrypt(P)$;
while $i < n$ **do**
  $temp = EvalMult(P_i, S_i)$;
  $C = EvalAdd(C, temp)$;
  i++;
end
$Decrypt(C)$;

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