MPC-Pipe: an Efficient Pipeline Scheme for Secure Multi-party Machine Learning Inference

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Abstract—Multi-party computing (MPC) has been gaining popularity over the past years as a secure computing model, particularly for machine learning (ML) inference. Compared with its competitors, MPC has fewer overheads than homomorphic encryption (HE) and has a more robust threat model than hardware-based trusted execution environments (TEE) such as Intel SGX. Despite its apparent advantages, MPC protocols still pay substantial performance penalties compared to plaintext when applied to ML algorithms. The overhead is due to added computation and communication costs. For multiplications which are ubiquitous in ML algorithms, MPC protocols add 32x more computational costs and 1 round of broadcasting among MPC servers. Moreover, ML computations that have trivial costs in plaintext, such as Softmax, ReLU and other non-linear operations become very expensive due to added communication. Those added overheads make MPC less palatable to deploy in real-time ML inference frameworks, such as speech translation.

In our studies, we found that most MPC protocols today perform communications and computations in sequential manner. This serialization is not a poor implementation choice, but a requirement for MPC to work correctly. Without the data communication the parties cannot progress to the next computation step. Thus GPU servers that are parties in an MPC setting are idle when waiting for data transmission to complete. During communication phase, GPU utilization is low. This phenomenon inspires us to enable MPC servers to perform computations and communications concurrently through a series of novel MPC-abiding computation transformation. In this work we present MPC-Pipe, an MPC pipeline inference technique that uses two ML-specific approaches. 1) inter-linear-layer pipeline and 2) inner layer pipeline. The first scheme benefits linear layers by transmitting input-independent MPC metadata beforehand, and the second benefits non-linear layers by breaking big inputs into smaller ones to overlap communications and computations. Those two techniques combined shorten the total inference runtime for machine learning models. Our experiments have shown to reduce ML inference latency by up to 12.6% when model weights are private and 14.48% when model weights are public, compared to current MPC protocol implementations.

I. INTRODUCTION

Due to the large amount of available hardware resources and cost-effective rental pricing, cloud computing has become more and more popular. Many companies have off-loaded their tasks related to machine learning to cloud servers hosted by cloud service providers like Amazon, Microsoft, Google, etc. For instance, companies such as Amazon provide ML model as a service in the cloud and individual entities may use those services to automatically process images and translate sentences. Those inputs to machine learning models can be closely related to an individual and privacy sensitive. Leaks and abuses of that information can negatively impact an individual’s trust in cloud. Thus, there exists an urgent need to protect input privacy in online machine learning tasks.

Many confidential computing techniques have been proposed to address the need for input privacy. Homomorphic encryption (HE) [8], trusted execution environments (TEE) [12], [15], [23], [26], [29], [30] and their extensions have been proposed. HE is based on modern cryptography and has strong mathematical proof for privacy. However, HE’s computation overhead at best is two orders of magnitude slower than plaintext, making it less palatable to deploy in real-time. On the other hand, TEEs usually rely on secure memory controllers that provide a trusted region in the main memory where accesses to those regions are strictly checked to prevent unwanted accesses by unauthorized parties. However, TEEs rely on trusting their hardware manufacturers, and manufacturers’ attestation services. Moreover, TEE implementations are not 100% robust. Implementation bugs and side channels can compromise input security [11], [33]. MPC [10], like HE, has a rigorous mathematically proven security guarantee, which is much stronger than TEE, but has fewer overheads than HE. MPC does not need to trust any manufacturer and attestation service providers. MPC can also tolerate a subset of compromised MPC servers. However, it does require additional computation and communication resources to perform the protocol, thereby making MPC still a relatively slow approach over plaintext. The goal of this paper is to tackle this challenge.

A. Key Observation about MPC

MPC protocols allow an MPC client to distribute its operands securely to a group of MPC servers (greater or equal to 2). MPC servers will operate on their local shares of operands and only communicate with each other when permitted by the protocol (more details in the next section). In most recent MPC frameworks [20], [21], [28], both communications and computations are blocking. While an MPC server is waiting for communication to complete, its GPU utility is very low. This phenomenon is especially true for communication-dominated layers like Softmax and ReLU [3].
While MPC servers perform computations, communication channels between MPC servers are completely idle, especially for computation-intensive layers such as Convolution and Dense layers. We present a set of ML-specific enhancements to the MPC implementation to improve this bottleneck. When MPC servers are waiting for the computations or communications, MPC servers could utilize their idle GPUs or communication channels to perform other tasks to reduce total inference latency.

### B. Pipeline Scheme

With the key observation in mind, we break MPC inference into two pipeline stages: the computation stage and the communication stage. We propose two main pipeline schemes for MPC ML inferences: 1) **inner-layer pipeline** and 2) **inter-layer pipeline**. MPC protocols use Beaver triples to assist multiplications and AND (more details in section II). For general Beaver triple assisted protocols, to perform multiplications or AND operations, MPC servers need to broadcast metadata related to both operands to other MPC servers before proceeding with computations. For linear layers such as Convolution and Dense layers, one of the operand-related metadata (the weight) is not input dependent because layer weights are static during inference. Thus, sending the input-independent metadata can be overlapped with computations to reduce the total inference runtime. For non-linear layers such as Softmax and ReLU layers, no input-independent metadata exists, and inter-layer pipeline cannot benefit non-linear layers. To achieve communication and computation overlap, we propose to divide large inputs into $n$ smaller pieces. While computing for piece $i$, MPC servers can send metadata related to piece $i + 1$ to reduce inference latency. Besides those general techniques, for the inner-layer pipeline, we use load-balancing to boost pipeline benefits further.

With the pipeline scheme described above, we can achieve MPC inference latency reduction for both CNN-based models and Transformer-based models. In our experiment setting, MPC-Pipe can achieve inference runtime reduction up to 12.6% for models with private weights and 14.48% for models with public weights.

### II. Background

#### A. General Multiparty Computing Description

This section will provide a general overview of MPC protocols. MPC involves two groups of participants: an MPC client and MPC servers. An MPC client is the entity that wishes to offload computation on their private data to cloud servers. MPC servers are the untrusted cloud servers that will perform computation specified by the MPC protocols. In this work, we adopt the semi-honest threat model where MPC servers will do the exact what MPC protocols specify, but they are curious about the data MPC clients are holding. Secure MPC computation model involves three steps:

1) MPC clients distribute operands to MPC servers in secret shares.

2) MPC servers compute on their own secret shares.

3) MPC clients retrieve the final result using results from MPC servers.

Figure 1 illustrates those three steps to compute $W \times X$. The MPC client firstly convert both into operands into 2 secret shares: $W \rightarrow [w_1], [w_2]$; $X \rightarrow [x_1], [x_2]$. Each secret share should not leak any information about the original $W$ and $X$. When MPC servers receive their local shares, MPC servers will proceed to compute their local share of $Y$ so that, after the MPC client retrieves $[y]$s, it can obtain $Y = W \times X$.

![Fig. 1. A 2-PC system example.](image)

#### B. Secret Sharing

Operands are distributed to MPC servers in the format of secret shares, and any secret shares sent to MPC servers should leak no information about the original operand $X$. There are two major ways to share an operand $X$ to $N$ MPC servers: additive and binary sharing.

1) Additive (arithmetic) sharing: An MPC server $i$ will receive

$$[x_i] : X = \sum_{i=0}^{N-1} [x_i]$$  

from MPC clients.

2) Binary sharing: An MPC server will receive

$$\langle x_i \rangle : X = \bigoplus_{i=0}^{N-1} \langle x_i \rangle$$  

from MPC clients. $[x_i]$ represents the additive secret share of original operand $X$ in the MPC server $i$, and $\langle x_i \rangle$ represents the binary secret share of original operand $X$ in the MPC server $i$. In latter sections, if subscript is not specified, $[x]$ and $\langle x \rangle$ represent secret shares of operand $X$ in MPC servers as a whole.

For example, in the 2PC setting, two additive shares of $X$ can be $[x_0] = X - R$ and $[x_1] = R$, where both $X$ and $R$ are in the same algebraic number field, and $R$ is sampled from a uniform random variable. The uniformity of $R$ renders
both $R$ and $X - R$ leaking no information about the original operand $X$. In the same 2PC setting, two binary shares for $X$ can be $(x_0) = X + R$ and $(x_1) = R$, where both $X$ and $R$ are in the same algebraic number field, and $R$ is sampled from a uniform random field. The uniformity of $R$ again renders both $R$ and $X + R$ leaking no information about the original operand $X$. Usually, the additive sharing format is more suitable for multiplications and additions, and the binary sharing format is more suitable for bit-wise operations like XOR and shifting. In the MPC example from figure 1 both operands $W$ and $X$ are shared in additive format: $|w_1| + |w_2| = W$ and $|x_1| + |x_2| = X$.

After distribution of secret shares, it’s MPC servers’ turn to run computations on their local shares. The next several sections will describe protocols to compute multiplications, bit-wise operations, several non-linear operations, and secret share format conversions.

C. Beaver Triple assisted Protocols

For operations such as additions and XORs between $X$ and $Y$, MPC servers just need to add or XOR their own local shares:

$$\sum_{i=0}^{N-1} x_i] + [y_i] = \sum_{i=0}^{N-1} x_i] + \sum_{i=0}^{N-1} [y_i] = X + Y$$  \hspace{1cm} (3)

$$\bigoplus_{i=0}^{N-1} \langle x_i \rangle \oplus \langle y_i \rangle = \bigoplus_{i=0}^{N-1} \langle x_i \rangle \oplus \bigoplus_{i=0}^{N-1} \langle y_i \rangle = X \oplus Y$$  \hspace{1cm} (4)

However, similar rules do not apply to multiplication and AND operations. In MPC, those operations are assisted by Beaver triples. Since AND operations for binary shares are equivalent to multiplications for additive shares, the latter sections will only show protocols for multiplications for conciseness. To derive MPC AND algorithm, one needs to replace every addition with XOR and every multiplication with AND in algorithm 1.

1) Beaver Triple: Beaver triples are three numbers in the same numerical field such that $C = A \cdot B$, and the triple is additively shared to MPC servers. Those triples are useful to compute $X \cdot Y$ in additive shares. Each MPC server will need to follow algorithm 1.

For MPC clients to recover the final product of multiplication, they need to sum all the $[z_i]$s from MPC servers. It is easy to see that:

$$\sum_{i=0}^{N-1} [z_i] = \sum_{i=0}^{N-1} [c_i] + (X - A)[b_i] + (Y - B)[a_i]$$

$$+ (X - A)(Y - B)$$

$$= C + XBY - AB + YA - BA + XY$$

$$- XBY - YA + AB$$

$$= XY$$  \hspace{1cm} (5)

Note that both $A$ and $B$ are sampled from a uniform random variable such that $X - A$ and $Y - B$ leak no information about $X$ and $Y$.

D. MPC Comparisons

Comparison in the MPC setting is not trivial. Less than is computed by $MSB([x_i] - [y_i])$, where $MSB$ is the function to obtain the most significant bit. As we mentioned earlier, bit-wise operations like shifting are more efficient in the binary sharing format. Thus, MPC servers need to convert $[x_i] - [y_i]$ to binary sharing format. Algorithm 2 shows such conversion.

Algorithm 2 Additive Share to Binary Share Conversion

**Input:** $[x_i]$  
**Generate binary shares** $\langle [x_i] \rangle : [x_i] = \bigoplus_{j=0}^{N-1} \langle [x_i] \rangle_j$  
**Send** $\langle [x_i] \rangle_j$ to party $j$  
**Wait until all** $\langle [x_i] \rangle_j$ are received  
**Use binary operations to compute** $\langle x_i \rangle = (\sum_{j=0}^{N-1} [x_i])$  
**Return** $\langle x_i \rangle$

The first two lines in algorithm 2 are steps for each MPC server to share its $[x_i]$ to other MPC servers in binary sharing format. Upon completion of this step, each MPC server will have a binary share for every additive share of original operand $X$. In the last step of algorithm 2, each MPC server will need to perform a series of AND and XOR operations (bit-wise logical only) to obtain the summation of binary shares. Such logical operations can be found in hardware adders like ripple carry adders and look-ahead adders (35). In the MPC framework our work based on, ReLUs and Maximum functions all use algorithm 2 to perform conversions to obtain the most significant bit.

E. Non-linear MPC Protocols

Besides multiplications and comparisons, there is a class of non-linear operations that is very important to machine learning workloads: exponential and reciprocal operations. Exponential functions are commonly used in Softmax, and reciprocal functions are used to compute division in MPC. Those non-linear operations are approximated using linear operations. For example, exponential functions are approximated by:

$$e^x = \lim_{n \to \infty} \left(1 + \frac{x}{2^n}\right)^{2^n}$$  \hspace{1cm} (6)
where \( n \) is the total number of approximation iterations. Polynomial approximations like Taylor series are not used to approximate exponential functions because exponential functions grow much faster than polynomial functions. Using polynomial functions will result in large error \([20]\).

Reciprocal functions can be approximated by:

\[
\frac{1}{x} = \lim_{n \to \infty} y_n = y_{n-1}(2 - xy_{n-1})
\]

where \( y_0(x) = 3e^{0.5-x} + 0.003 \) \([20]\).

\( F \). Numerical Instability in the Softmax

Softmax functions in Machine Learning are used to create separation between input values. Softmax function for the \( i \)th element in a given vector is defined as:

\[
\text{Softmax}(x_i) = \frac{e^{x_i}}{\sum_{k=0}^{n-1} e^{x_k}}
\]

The exponential function in the Softmax can explode quickly causing floating point overflow \((x \geq 100)\). Thus, practical implementations introduce the maximum value in the given vector to stabilize the exponential function defined below:

\[
\text{Softmax}(x_i) = \frac{e^{x_i - x_{\text{max}}}}{\sum_{k=0}^{n-1} e^{x_k - x_{\text{max}}}}
\]

where \( x_{\text{max}} \) is the maximum value in the given vector. The introduction of the \( x_{\text{max}} \) as a stabilizer forces inputs to exponential functions at most 0 preventing numerical overflow. Nevertheless, according to our experiences with machine learning inference, for plaintext insecure inferences using single-precision floating points, inputs to exponential functions are small so that the \( x_{\text{max}} \) can be omitted. However, according to a recent study for MPC Transformer-based models \([34]\), due to MPC numerical limitations and linear approximations, using the \( x_{\text{max}} \) is vital to model performance accuracy. Omitting or replacing the \( x_{\text{max}} \) to stabilize exponential functions can destroy model accuracy.

\( G \). Transformers

Transformers are gaining popularity in recent years due to their abilities to encode dependencies between inputs \([31]\). Transformers are wildly used in the field of Natural Language Processing \([4, 6, 22, 24]\), and computer vision \([7]\). Given their popularity, we’d also like to evaluate MPC-Pipe on Transformers. Thus, this section will discuss the Transformer-based model architecture. Figure 2(a) and (b) shows general architecture of Transformer-based NLP and vision model, and figure 2(c) shows a Transformer layer. In Transformers, there are two major computation blocks: multi-head attention and feed forward. Figure 2(d) and (e) show the detailed computation decomposition of a multi-head attention layer. The multi-headed attention is mathematically defined as:

\[
\text{Attention}(V, K, Q) = \text{Softmax}(\frac{QK^T}{s})V
\]

And, the feed forward layer in Figure 2(c) is mathematically defined as:

\[
\text{FFN}(x) = \text{Dense}(\text{Act}([\text{Dense}(x)])
\]

where “Act” is an activation function which be either ReLU and GeLU.

\( III \). MPC-Pipe

In MPC-Pipe, we propose an MPC pipeline framework that allows model inference to run in an efficient pipeline. There are two major pipeline schemes in MPC-pipe: 1) inter-linear-layer pipeline and 2) inner layer pipeline. The first scheme is mainly for linear operations, and the second scheme is mainly for non-linear operations. The next several sections will elaborate on each pipeline scheme.

\( A \). Inter-linear-layer pipeline

There are two major classes of linear operations in the machine learning workloads: Dense operations and Convolution operations. During linear layer inference, a function of model \( X \) and weights of the layer \( W \) is calculated. According to section II-C before performing heavy linear operations on the weights and inputs, MPC servers have to broadcast their local shares to reveal \( X - A \) and \( W - B \), where \( A \) and \( B \) are part of a Beaver triple. In the current MPC framework, GPUs in MPC servers are completely idle during the broadcasting. Indeed, without \( X - A \) and \( W - B \) from the current layer, latter heavy linear operations cannot proceed. However, the metadata \( W - B \) is completely input-independent. Computing and broadcasting \([w] - [b]\) does not need to happen after the previous layer to finish computing the result. Thus, we can overlap computing final \([z]\) for the previous linear layer with broadcasting \([w] - [b]\), shortening the critical path. Therefore, every linear layer, before computing the final \([z]\), can begin to transmit \([w] - [b]\) of the next linear layer to other parties. Figure 3 shows the timing diagram of inter-linear-layer pipeline. The red block represents the computation runtime, and blocks in other colors represent the communication runtime. Inter-layer pipeline breaks communication block into two parts. One part is transmitting input-dependent \((X)\) metadata, and the other is transmitting input-independent \((W)\) metadata. For L=0 in the figure 3, it overlap the transmission time of the L=1 metadata with its computation time. In this way, the latency of each layer is reduced.

\( 1) \) Implementation: For a machine learning model to benefit from the inter-linear-layer pipeline, MPC-Pipe needs to know the dimensions of weights and layer configurations for every linear layer. To obtain such information, MPC-Pipe must first run models in the non-pipeline setting. Then, later inference runs will be in the pipeline setting.

The inter-linear-layer pipeline version of algorithm 1 is implemented as:

```python
1 def inter_beaver_multiplication(x, y):
2     # obtain beaver triples
3     a, b, c, delta = obtain_current_beaver_triple()
4     # revealing X-A using async calls
```
Fig. 2. Transformer-based model computation graph decomposition: (a) General structure of XLM; (b) General structure of a ViT; (c) A Transformer; (d) Multi-headed attention; (e) Scaled dot-product attention.

Fig. 3. Inter-linear-layer pipeline demonstration.

| Line | Code | Description |
|------|------|-------------|
| 6 | epsilon = x - a | Asynchronous transmission of epsilon = x - a. |
| 7 | req_x = comm.get().allReduceAsync(epsilon) | Asynchronous transmission of epsilon. |
| 8 | # transmitting next layer metadata | Transmission metadata. |
| 9 | if next_linear_exists(): | Check if next layer exists. |
| 10 | a1, b1, c1 = obtain_new_beaver_triple() | Obtain Beaver triple for next layer. |
| 11 | next_y = obtain_next_y() | Obtain next layer metadata. |
| 12 | next_delta = next_y - b1 | Compute next delta. |
| 13 | # transmit | Transmit metadata. |
| 14 | next_req = comm.get().allReduceAsync(next_delta) | Asynchronous transmission of next_delta. |
| 15 | set_next_triple(a1, b1, c1, next_delta) | Set Beaver triple for next layer. |
| 16 | set_next_req_y(next_req) | Set next request. |
| 17 | req_y = obtain_cur_req_y() | Obtain current request. |

Line 7 begins the asynchronous transmission of $\epsilon = x - a$, and line 16 begins the asynchronous transmission of $\text{next}_{\text{delta}} = \text{next}_{\text{y}} - b1$ for the next layer. In our implementation, $\delta$ is the input-independent metadata, and $\delta$ can be pre-computed and pre-transmitted. Line 11-13 are obtaining Beaver triples for the next layer, and its runtime is overlapped with the transmission of $\epsilon$ as well. Surprisingly, the inter-linear-layer pipeline also hides the input-dependent metadata transmission with Beaver triple generations. Line 24-25 is waiting for the transmission of $\delta$ and $\epsilon$, without which lines 28-30 cannot proceed. Because of our pipeline, the wait time for Beaver triple metadata transmission is almost 0 for linear operations.

B. Inner-layer pipeline

There is no opportunity to exploit the inter-layer pipeline for functions whose only operand is dependent on the original inputs. Metadata that MPC servers need to transmit will only be available after the previous layer finish computing its final $z$. Thus, to overlap communications with computations, we must search within each layer. Softmax, ReLU, and Maxpooling layers are such layers whose operands are input-dependent, and we need to find parallelism within those layers. According to our analysis, the inference runtime of those operations is dominated by comparisons. As we mentioned in section II, comparisons require secret sharing format conversions, and such conversions will involve performing many AND operations (binary adders). Like multiplications for additive shares, AND operations are also assisted by Beaver triples.
AND operations are element-wise operations, which means computing AND for any element in a given vector does not require metadata from other elements. However, in the current blocking implementation, all elements in the vector are waiting for metadata related to other elements, even its metadata has already been transmitted and available. Thus, we divide inputs into smaller batches. Before performing computation for batch #i, MPC servers will initiate the transmission process for batch #i + 1. In this way, batch #i does not have to wait for metadata that is not related to its computation. Figure 4 shows the timing diagram of the inner-layer pipeline and how the latency for AND operations changes. As before, the red blocks represent computation runtime, and blocks in other colors represent communication runtime. After pipeline, computation of batch #i is overlapped with communication of #i + 1. By using the inner-layer pipeline, MPC servers can proceed to compute with a part of the larger input without wasting time waiting for unrelated metadata. Note that the ratio between computation and communication is not at scale in the figure.

1) Implementation: For the inner-layer pipeline to benefit a machine learning model, MPC-Pipe requires no additional information from the models themselves. The inner-layer pipeline version of AND operator is shown below:

```python
1 def inner_beaver_AND(x, y):
2     # obtain old dimension of inputs
3     oldView = x.size()
4     # reshape inputs into smaller blocks
5     x = changeView(x)
6     y = changeView(y)
7     # obtain the result buffer
8     res = crypten.zero_like(x)
9
10     # lists keeping track of metadata
11     req0List = []
12     ...
13     delList = []
14
15     # transmitting metadata
16     for i in range(x.size(0)):
17         a, b, c = obtain_beaver_tripple(x[0].size(), y[0].size() )
18         # transmitting metadata
19         epsilon = x[i] ˆ a
20         delta = y[i] ˆ b
21         req0 = comm.get().allReduceAsync(epsilon)
22         req1 = comm.get().allReduceAsync(delta)
23         # metadata management
24         aList.append(a)
25         ...
26         delList.append(delta)
27     for i in range(x.size(0)):
28         req0List[i].wait()
29         req1List[i].wait()
30         res[i] = (bList[i] & epsilonList[i]) ˆ (aList[i] & delList[i]) ˆ (epsilonList[i] & delList[i]) ˆ cList[i]
31
32     return res.view(oldView)
```

Inner-layer pipeline differs from the original beaver protocol because it breaks the input to multiply smaller blocks. In the algorithm 1, MPC servers are waiting for broadcasting of epsilon and delta before computing. In contrast, MPC-Pipe breaks the transmission of a large chunk of data into transmissions of several smaller data blocks (lines 18-32). Thus, some computation can proceed while MPC servers transmit other smaller blocks. Line 35-36 only waits for the transmission of a smaller block, which are overlapped with the computation of another smaller block.

2) Load-balancing the Set-Propagate-Kill Tree circuit: AND operations, compared with Dense and Convolution operations, are relatively fast to compute. During our early explorations, hiding latency for AND operations specified by Beaver triple assisted protocols resulted in a little performance improvements. However, the Set-Propagate-Kill (SPK) Tree circuit used during secret sharing conversion allows us to better balance the pipeline. This circuit involves sequentially evaluating six AND operations, and some other logical operations are proceeding each AND operation. SPK tree circuit logic is shown:

```python
1 def SPK_circuit(S, P):
2     mask, out_masks, mult = SPK_constants()
3     SIP1 = stack(S, P)
4     for i in range(6):
5         in_mask = mask[i]
6         out_mask = out_masks[i]
7         # constants
8         not_out_mask = out_mask ˆ -1
9         P0 = SP[i] & out_mask
10         SIP1 = SP & in_mask
11         SIP1 = mult[i]
12         update = P0 & SIP1
13         res[i] = (bList[i] & epsilonList[i]) ˆ (aList[i] & delList[i]) ˆ (epsilonList[i] & delList[i]) ˆ cList[i]
14
15     return res.view(oldView)
```
Lines 9-12 are logical operations that only need to operate on MPC servers’ local shares without metadata transmissions because variables returned by function $SPK_{\text{constants}}$ are all constants in plaintext. The only logical operation in the for loop that requires Beaver triples is in line 14. In our implementation, we move logical operations in lines 9-12 to the computation stage of $\text{AND}$ operation in line 14, achieving a better balanced pipeline. We call the modified $\text{AND}$ operation in line 14 as $\text{mergedAND}$. The implementation of $\text{mergedAND}$ is very similar to that of pipelined $\text{AND}$ shown in the previous section except for added $SPK$ constant logical operations.

3) Size matters: During our experiment, there exists an input size threshold below which the inner-layer pipeline shows no advantage. Because logical operations on 64-bit integers are not too computationally intensive, for inputs of small sizes, dividing inputs into multiple even smaller blocks actually increases the total computation time. Smaller data blocks cannot saturate the computational units in GPUs, resulting in longer computation runtime. Since input size is small, the total inference runtime is dominated by computations, and longer computation time results in longer total inference runtime. In our experimental setups, we found that the inner-layer pipeline for input size smaller than 2MB shows no benefits. Our framework automatically disables the pipeline in such a case.

C. Applicability to ML Models

Table I shows the applicability of pipeline schemes for each machine learning operation. For Convolution and Dense, the inter-layer pipeline is applicable because their weight metadata is not input-dependent, which can be transmitted beforehand. On the contrary, the inter-linear-layer pipeline does not apply to ReLU, Softmax, and Maxpooling since every operand of those operations is input dependent, whose metadata is only available when previous operations finish. As for the Multi-headed Attention layer in Transformers, both inter-layer and inner-layer pipeline schemes are applicable. According to figure [1(e)], both Dense and Softmax operations exist in the Multi-headed Attention layer. The two matrix multiplications inside Multi-headed attention can only use the inner-layer pipeline because they do not use any static weight as their inputs.

| Pipeline Applicability for Machine Learning Operations. |
|----------------|----------------|----------------|
| Convolution    | ✔              | ✔              |
| Dense          | ✔              | ✔              |
| ReLU           | ✔              |                |
| Softmax        |                | ✔              |
| Maxpool        |                | ✔              |
| Attention      | ✔              | ✔              |

Inside Softmax functions, there are exponential functions, and exponential functions are approximated using multiple iterations of squaring operations. Compared with normal multiplications, squaring operations have fewer communication overheads since they are unitary operations. Squaring also benefits from the inner-layer pipeline like ReLUs.

D. Steps to apply MPC-Pipe

For a model to benefit from MPC-Pipe, two steps are required: 1) informing MPC-Pipe about the dimensions of model weight and input, and 2) measuring the threshold at which the inner-layer pipeline stops producing speedups. The first step requires programmers to run the model in the non-pipeline scheme once so that MPC-Pipe can capture the dimension of operands of linear operations. Without dimensional information, MPC-Pipe cannot generate suitable Beaver triples and cannot pre-transmit metadata. The second step requires programmers to run non-linear layers inside their models with various input dimensions to determine the threshold for their systems. MPC-Pipe might adversely impact model performance without threshold measurements due to the small intermediate size.

IV. Evaluation

A. Experimental Setups

We have evaluated our design on servers with Intel Xeon Gold 5220R CPU and an Nvidia Quadro RTX 5000. The bandwidth between server nodes is 10Gb/s. However, the peak bandwidth we observed is about 8Gb/s. Implementation of MPC-Pipe is based on CrypTen [20], an MPC framework based on Pytorch from Meta AI. We gather inference runtime from the average of 50 iterations of inferences so that the improvement we will show actually comes from MPC-Pipe instead of network fluctuations.

B. Methodology

We evaluate MPC-Pipe in the 2PC and 3PC settings, where the number of MPC servers is 2 and 3, respectively. We believe that 2PC and 3PC provide robust security model tolerating 1 and 2 compromised MPC servers while keeping the hardware costs and the performance overheads low. We believe 2PC and 3PC are more likely to be deployed in a real-life setting. Although we did not evaluate MPC-Pipe in 3+PC, we provide a quantitative analysis of MPC-Pipe scaling to more parties in section IV-F.

1) Models evaluated: We evaluated MPC-Pipe on two major Machine Learning workloads: 1) a Transformer-based model and 2) Convolution Neural Networks. The Transformer architecture we selected is the one used in popular Natural Language Processing models [4], [6], [22], [24], and the CNN models we selected are VGG16 [27] and ResNet50 [13].

2) Public model: Besides evaluating MPC-Pipe in the setting that treats model parameters are privacy sensitive (private model), we will also show the MPC-Pipe performance benefit when model parameters are publicly available. Companies and researchers have been publishing their model weights for many
years. Many of those models have great performances. Thus, people can deploy MPC on models whose parameters are non-privacy sensitive. If weights are public, for Convolutions and Dense operations, there is no need to use Beaver triple assisted multiplication. MPC servers just need to multiply the public weights with the inputs’ local secret shares. It is easy to see that

\[ \sum_{i=0}^{N-1} W \cdot [x_i] = W \cdot \sum_{i=0}^{N-1} [x_i] = W \cdot X \]  

(12)

Consequently, the inference runtime for Convolution and Dense operations becomes as fast as their non-secure counterparts. Thus, public weight inference could become popular due to reduced overheads. We also evaluated MPC-Pipe in this setting.

C. Operations using single precision floating points

Previous frameworks like CrypTen and CryptGPU run matrix multiplication related operations on double-precision floating points (float64) [20], [28]. They also use 64-bit fixed point to implement operands in the numerical field. In [20], [28], 64-bit operands are broken into four 16-bit smaller blocks, and each block is stored in a float64. Because float64 has 52 bits for fractions, four 16-bit blocks are the most ideal allowing \(2^{52-16} = 2^{36} \) accumulations after multiplications. However, for most GPUs, the number of 32-bit floating point multipliers is more than that of 64-bit floating point multipliers. For computational intensive operations like convolutions, we found that it is much more efficient to use 32-bit floating point to compute convolutions. Thus, in our experiments, 64-bit operands are broken into 16 4-bit smaller blocks to use 32-bit floating point multipliers. Float32 has 22 bits as fraction, and multiplication between 2 4-bit operands require 8 bits to store the product. Thus, it leaves us \(22 - 8 = 14\) bits for accumulation, which is also enough for the models we have tested on MPC-Pipe.

In our experimental setup, we found that using float32 can improve the inference runtime of the Convolutional network by roughly 3x compared to using float64, but using float32 fail to improve the Dense operations. This phenomenon results from computational unit saturation. Most GPUs have more 32-bit multipliers than 64-bit multipliers. Convolutions, having lots of multiplications, saturate both 32-bit and 64-bit multipliers. Since GPUs have more 32-bit multipliers, using float32 to compute Convolutions results in shorter latency. However, Dense operations, due to fewer number of operations, cannot saturate 32-bit and 64-bit multipliers. The inference runtime for both operations is comparable using either bit-width multiplier. Thus, using float32 shows no inference runtime improvement for Dense operations. In our experiments in later sections, Convolutions are computed using float32, and Dense operations are computed using float64.

D. Private Weights

In this section, we will firstly present data for private weights where model parameters are also privacy sensitive.

In this setting, MPC clients also wish to protect the model parameters and distribute model weights in secret sharing format to MPC servers. All computations in this setting will follow MPC protocols: multiplications and \(AND\) will have to use Beaver triples.

1) Transformers: We break Transformer computations into four main categories: 1) Linear, 2) Softmax, 3) ReLU, and 4) Attention. Softmax and ReLU categories are self-explanatory. Attention category includes the two matrix multiplications in figure 2(e). The linear category includes all other matrix multiplications in the Transformers. The Linear operations in the Transformers mainly benefit from the inter-linear-layer pipeline. All the Linear layers will begin to transmit weight related metadata for the next linear before proceeding with computations. Other operations mainly benefit from the inner-layer pipeline. Both Softmax and ReLU operations benefit from load balancing due to their use of the SPK circuit.

Figure 5 shows speedups for each components of Transformers. The left part shows the speedups in the 2PC settings, and the right part shows the speedups in the 3PC setting. MPC-Pipe brings 8.19% speedup in the 2PC setting and 12.60% speedup in the 3PC setting. Linear operations experience only a less speedup due to the small matrix size. The only linear operations in the Transformers are Dense operations. Computations are dominating the inference runtime for Dense operations. Communication for Dense layers, roughly, accounts 8% of total inference runtime. Thus, even for the best pipeline scheme, we should not expect speedup to be more than that. The operations in the Attention category experience the most speedup due to their balance computation and communication runtime distribution; latency hiding is most effective in such a case. Softmax functions experience less speedup than the ReLU in Transformers, although most of their runtime is spent on comparison circuits. The threshold for the inner-layer pipeline causes this phenomenon. Softmax functions need to compute a maximum in the last dimension of their
inputs. To compute the maximum of a large vector, we use log reduction maximum. As maximum functions are approaching completion, the dimension of inputs to SPK circuits becomes smaller. The inner-layer pipeline has been disabled during the last several iterations. Thus, not all SPK circuits in Softmax functions enjoy the inner-layer pipeline resulting in fewer speedups than ReLU functions.

2) **CNN Models:** We break computations of CNN models into three main categories: 1) Linear, 2) ReLU, and 3) Maxpooling. For CNN models, the Linear category contains Convolution layers in feature abstraction layers and Dense layers in classifiers. Most of the Linear layers are Convolutions. There are only 3 and 1 layers in ResNet50 and VGG16, respectively, and other categories are self-explanatory. Note that VGG16 has 5 Maxpooling layer, whereas ResNet50 has none.

![Fig. 6. MPC-Pipe Speedup for private model VGG16.](image)

Figure 6 and figure 7 shows the speedup breakdown of MPC-Pipe for VGG16 and ResNet50 respectively. The left part shows the speedups in the 2PC settings, and the right part shows the speedups in the 3PC setting. For VGG16, MPC-Pipe brings 7.31% speedup in the 2PC setting and 9.97% speedup in the 3PC setting. For ResNet, MPC-Pipe brings 8.32% speedup in the 2PC setting and 10.23% speedup in the 3PC setting. Linear operations mainly benefit from the inter-layer pipeline to hide communication of weight metadata, whereas Maxpooling and ReLUs benefit mainly from the inner-layer pipeline. Every computational category experiences more speedup in the 3PC setting than in the 2PC setting. In the 3PC setting, there is one extra MPC server. While broadcasting metadata, MPC servers must send extra data to the added server. Computation costs with more parties will also increase since more resources are required to aggregate secret shares from other parties. With the increase in both communication and computational costs, pipeline can be better balanced for every operator inducing more speedup in the 3PC setting than that in the 2PC setting.

![Fig. 7. MPC-Pipe Speedup for private model ResNet50.](image)

**E. Public Weights**

This section shows the performance benefit of MPC-Pipe when model weights are public. Both academia and industry have kept publishing their novel models and their weights, and many publicly available weights have good performances. When MPC clients deploy models whose weights are already publicly available, protecting those parameters is expensive and unnecessary. When MPC clients do not protect the weights, they will distribute them in plaintext, with no encryption. In this setting, linear operations do not need Beaver triples to assist their computation. The runtime of linear operations such as Convolution and Dense become their plaintext counterparts.

![Fig. 8. MPC-Pipe Speedup for public models.](image)
Figure 8 shows the speedups of MPC-Pipe when model weights are public for Transformers and CNN models. Similarly to the private weight setting, models experience more speedups in the 3PC setting. The reasoning is the same as that in the private model settings. In the public weight setting, models mainly benefit from the inner-layer pipeline since all the operations that require MPC protocols are Softmax, ReLU, Maxpool and Attention. All of those operations do not have input-independent operands, and MPC-Pipe cannot apply inter-layer pipeline to those operations.

\section*{E. Scaling beyond 3 parties}

The MPC protocols, on which our framework is based, are general protocols that can scale to multiple MPC servers. In the previous sections, we have demonstrated MPC-Pipe’s advantages in both 2PC and 3PC settings. Due to equipment limitations, we do not have MPC-Pipe’s benefit when there are more than 3 MPC servers. This section provides a qualitative analysis of MPC-Pipe’s benefit with more MPC servers participating.

![Graph showing speculated MPC-Pipe benefits with more parties.]

For a general pipeline scheme to have a significant benefit, neither pipeline stage should be insignificant compared with other stages. In MPC-Pipe, we break MPC protocols into two stages: 1) computation stage and 2) communication stage. Theoretically, in the ideal setting, the computation stage and communication stage account for half of the total inference time, and with a perfect pipeline, MPC-Pipe can achieve 2x runtime reduction. Nevertheless, it is not the case for most operations commonly found in machine learning workloads. For Linear operations like Convolution and Dense, communication roughly accounts for 10% total runtime in the 2PC setting. Even for the perfect pipeline, MPC-Pipe cannot have benefits above that threshold. For Softmax and ReLU, communication can account for 80% of total runtime in the 2PC setting. As we scale MPC servers to more parties, the communication cost grows quadratically since all communications in the Beaver triple assisted algorithm are broadcasting. In contrast, the increase in computation to accumulate secret shares only increases linearly. In our previous experiments, when scaling from 2PC to 3PC, the increase in communication and computation costs does not make operations more unbalanced. For Linear operations, due to the inter-layer pipeline, MPC-Pipe successfully hides more communication runtime. Communication and computation runtime distribution roughly stay the same. When scaling from 3PC to 4PC, we speculate Linear operations will continue to have more speedups because computation dominates Linear operations. More increases in communication cost will only render more speedups after pipeline. Non-linear layers will experience more communication increase, and MPC-Pipe’s benefit will decrease. However, due to an increase in the speedups provided by Linear operations in the 4PC setting, we expect MPC-Pipe’s performance improvements to stay roughly the same as one we see in the 3PC setting.

As for the 4+PC setting, we expect communication and computation distribution will become unbalanced, and most of the inference runtime will be spent on transmitting data. Thus, MPC-Pipe will have fewer speedups. As we scale to more and more MPC servers, the benefit might become insignificant. Figure 9 shows the speculated MPC-Pipe benefit we have discussed. However, when using 3+PC, the MPC protocol itself just becomes unforbearingly slow. Increased equipment costs and inference runtime might make increased security guarantees from additional MPC servers less palatable. When scaling more 2PC to 3PC, inference runtime has already increased by 1.8x, 1.65x, and 2.15x for ResNet50, VGG16, and Transformers, respectively. Scaling to more parties will make MPC inference quadratically slower. Thus, we do not think fewer performance improvements in 3+PC settings will reduce the real-life application of MPC-Pipe.

\section*{V. RELATED WORKS}

ABY \cite{5} proposes a 2PC mixed secret sharing (additive, binary, and Yao) framework and respective conversion algorithms. ABY3 \cite{25} proposes another mixed secret sharing framework for replicated MPC. Replicated MPC is a special form of MPC where each MPC server has multiple secret shares of operands. For example, in the 3PC setting, server1 has \([x_1]\) and \([x_2]\), server2 has \([x_2]\) and \([x_3]\) and server3 has \([x_3]\) and \([x_1]\), where \(X = [x_1] + [x_2] + [x_3]\). The threat model in this setting can only tolerate at most one compromised node. It has fewer communication overheads than the ABY, but it does not scale efficiently to tolerate more than 1 compromised node despite having 3 MPC servers. The efficient scaling of replicated MPC is still unknown to this day. Like CrypTen, the MPC framework this work is based on, MPC-Pipe focuses on the additive sharing and binary sharing proposed in ABY.

\section*{A. MPC Frameworks}

Falcon \cite{32} and CrypTFow \cite{21} are the first several works to demonstrate privacy-preserving ML on ImageNet. None of those two frameworks fully utilize the computational power
of GPUs. CrypTen \[20\], and CryptGPU \[28\] are MPC frameworks using two secret sharing schemes proposed in ABY \[5\] and ABY3 \[25\] respectively. Both frameworks enable MPC in Nvidia GPUs and share the same CUDA implementation. In both frameworks, communication and computation are blocking calls. This paper builds on top CrypTen and enables shorter MPC Machine Learning model inferences by overlapping communication and computation. PPLAC \[36\] is another MPC framework that introduces special hardware in MPC servers to reduce the communication costs for MPC protocols. PPLAC changes the threat model of MPC by bringing additional hardware into the trusted domain. In contrast, MPC-Pipe is a pure system modification that uses the semi-honest threat model specified in ABY.

B. MPC Operation Optimizations

Sphynx \[3\], DeepReduce \[14\], and Circa \[9\] has proposed optimizations to optimize MPC CNNs. \[34\] is an extensive study on MPC inference of Transformer-based models and urges for optimizations for MPC Softmax.

C. Other Privacy Preserving Frameworks

Besides MPC protocols, there exist other families of privacy-preserving ML frameworks. One of those families is based on the efficient distribution of workloads in trusted execution environments. \[26\], \[30\] are inference frameworks that utilize GPUs to speed up private inferences. They cannot be broadened to training. DarkNight \[12\] is a novel coding scheme that allows users to protect inputs during model training, and it has demonstrated its efficiency on deep networks.

Homomorphic encryption (HE) \[8\] is another popular privacy-preserving network, and a large body of literature exists to accelerate computationally heavy HE. \[1\], \[2\], \[17\] are HE acceleration based on CPUs. \[1\] focuses on utilizing multi-threading, whereas the other two focus on SIMD operations. \[16\], \[18\] are GPU-based HE acceleration and \[19\] is a recent hardware accelerator for HE.

VI. Conclusion

In this era of cloud computing, people are offloading computations to cloud servers, and demand for confidential computing is rising. MPC is one of the viable solutions to the urgent need for input privacy in cloud servers. Compared with other popular schemes like HE and TEEs, MPC has better inference runtime than HE because most of its operations computed by MPC servers are linear. MPC also has a more robust threat model than TEEs because MPC clients do not need to trust additional hardware and can tolerate a subset of MPC servers compromised. Nevertheless, MPC inference increases computation cost by 32x and induces communication costs between MPC servers.

In this work, we make a key observation that when MPC servers are transmitting MPC metadata during Machine Learning model inference, GPU utility is very low such that MPC could benefit from overlapping some of the computations with communications. Thus, we propose MPC-Pipe, an efficient pipeline scheme for secure MPC. In MPC-Pipe, we break MPC model inference into two stages: computation stage and communication stage; we also propose two key pipeline schemes: 1) inter-linear-layer pipeline and 2) inner-layer pipeline. The first scheme benefits Linear operations by transmitting input-independent MPC metadata for linear layers beforehand, and the second scheme benefits non-linear layers, where all the operands are input-dependent. Convolution and Dense operations benefit from the first scheme, whereas Softmax, ReLU, and Maxpooling operations benefit from the second approach. Besides those two general approaches, we also propose load-balancing and pipeline threshold to further boost the performance benefit of MPC-Pipe. We evaluate MPC-Pipe on popular models such as VGG16, ResNet50, and Transformers. We also demonstrate the persistent inference runtime reduction of MPC-Pipe. In certain configurations, MPC-Pipe can improve MPC model inference by up to 12.6% for models with private weights and 14.48% for models with public weights.
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