Indian Institute of Technology, Delhi

Privacy Preserving Machine Learning

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A report submitted in fulfillment of the requirements of M.Tech Project

in the

Department of Mathematics and Computing

October 28, 2021

Abstract

Air pollution is one of the main problems faced by Delhi today. Cab companies have a growing vehicle fleet which they are willing to instrument for measurements of traffic, air pollution etc. Analyzing fine-grained sensor data from such large fleets can be extremely beneficial, however, this sensor information reveal the locations and the number of vehicles in the deployed fleet. This sensitive data is of high business value to rival companies in the same business domain, e.g., Uber vs Ola, or Uber vs. Lyft in cab sharing domain or Amazon vs. AliBaba in e-commerce domain. To overcome this, past work (Prac2PC) looked at using secure 2-party computation like Yao's garbled circuits in order to preserve sensitive information as well as answer many practical queries. It allows a server to answer queries from users without providing exact data. In this project, we explore multi party secure computation using `Crypten` on various Machine Learning models like Graph Convolutioanl Network (GCN) and Gaussian Process (GP) based interpolation, so that different available servers can answer a query together and also jointly train on their data.

1 Machine Learnign Problem

Prof. Rijurekha Sen's team has been working to scale up Particulate Matter (PM) measurement using vehicle mounted sensors. Her team has a pilot deployment of pollution measuring sensors on 10 DIMTS buses (regions covered shown on the left) in Delhi that are able to record fine-grained particulate matter (PM) values (PM1.0, PM2.5 and PM10) along with GPS coordinates. While mobile sensors mean values are not collected at all places at all times, with state of the art spatio-temporal interpolation methods like Gaussian Processes and Graph Convolutional Neural Networks, values where no sensors are present at a particular time can be estimated. The mobile sensors, along with interpolation methods, can give much more fine-grained information, than the current 35 static pollution sensors, deployed by CPCB and DPCC to cover the huge geographical areas of Delhi-NCR. Thus the Machine Learning Problem of interest here is that of training spatio-temporal interpolation models from pollution data.

2 Privacy Problem

Privacy preserving ML is a very important research topic these days. For example, hospitals trying to train cancer detection using patient images, cannot share patient images with other hospitals to preserve patients' privacy. However, the trained model can be much better, if images of all hospitals could be fed into the training algorithm. In scaling the vehicle deployed pollution sensing to other fleet companies like Ola and Swiggy, Prof. Rijurekha's team is faced with a similar privacy concern. These fleet companies do not want to share their real time or historical GPS location traces, as that information is of high business value. Ola doesn't want Uber to know the Ola vehicle positions, Swiggy doesn't want Zomato to know the Swiggy vehicle positions. But for the training the spatio-temporal interpolation models for pollution, location-time and PM data collected by the fleets is necessary. Thus how to combine the data collected by different vehicle fleets for interpolation model training, while keeping the GPS location information private will be explored in this MTech Thesis.

3 Introduction

As stated earlier, the problem involves responding to client queries based on pollution data collected by various cab and delivery companies for a particular city. The client is interested in knowing the level of pollution on their route along with how reliable the information is. At the same time, the client doesn't want to share their exact location. Similarly, the companies want their sensitive data to be secure as it is possible to estimate their fleet location using confidence scores. The city is modelled as a grid with pollution values available for some grid points. Each company has a different set of pollution values for these points which are updated periodically. For the points where pollution values are not available we perform interpolation. There are two ways to do this — either each company can interpolate independently on its own data and the results from all companies can be combined or the interpolation can be performed jointly over the combined data all companies collectively have. The next step is to answer client queries using these interpolated values. The queries could be average or maximum pollution value on a path etc. Note that all joint computation must happen securely.

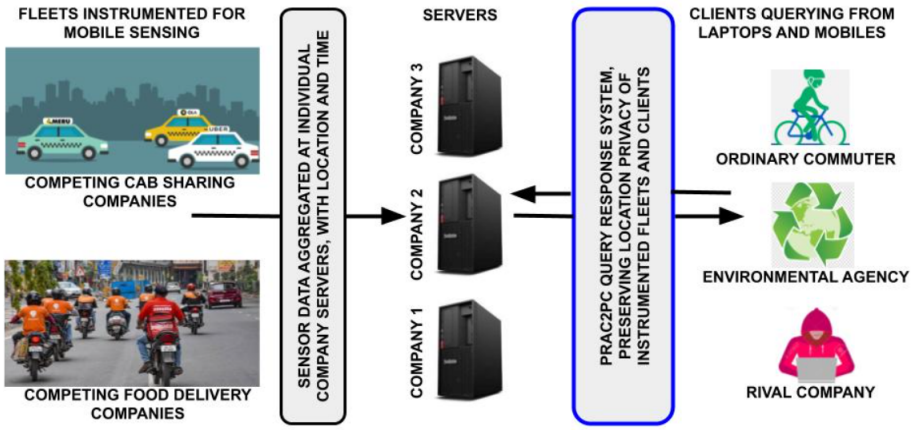

Figure 1: Overall Architecture

3.1 Prac2PC

In Prac2PC, a client could ask queries from only a single server. The client did so by engaging in a 2 party computation with the server by using Yao's garbled circuits. The server only performed interpolation on its own data which meant that these 2-party queries tend to be accurate only in areas where that particular cab company's fleet is located.

3.2 Extending Prac2PC to PracMPC

2-party secure communication protocols used in Prac2PC do not work for the multi-party setting and we needed to explore and use MPC protocols here. In the next section we will talk about the protocols used. We proceed with the project in two steps:

Figure 2: 2PC Interpolation

- We first only perform secure aggregation and query answering, where each server does interpolation independently on its own data. Here, we first need to merge pollution predictions from different servers for the same points and then answer client pollution queries.
- Then we extend this to secure interpolation across servers, where servers collectively interpolate their data and then securely answer queries. This problem was absent in the 2PC setting as there was a single server which did the interpolation. Also, joint interpolation may lead to better predictions for unknown locations.

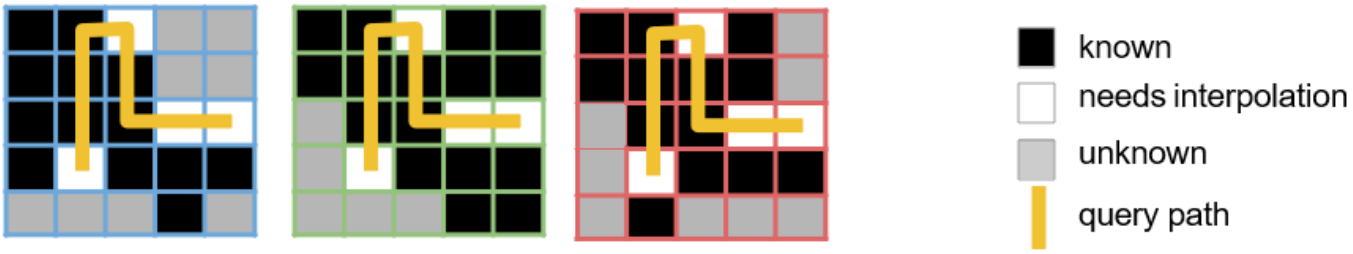

Figure 3: MPC Interpolation

4 Secure MPC Background

Secure multi-party computation is an abstraction that allows multiple parties to compute a function on encrypted data, with protocols designed such that every party is able to access only their own data and data that all parties agree to reveal.

Let's look at a concrete example to better understand this abstraction. Suppose we have three parties, A, B and C that each have a private number, and together want to compute the sum of all their private numbers. A secure MPC protocol for this computation will allow each party to learn the final sum; however, they will not learn any information about the other 2 parties' individual private numbers other than the aggregate sum.

In secure MPC, the data owner encrypts its data by splitting it using random masks into n random shares that can be combined to reconstruct the original data. These n shares are then distributed between n parties. This process is called secret sharing. The parties can compute

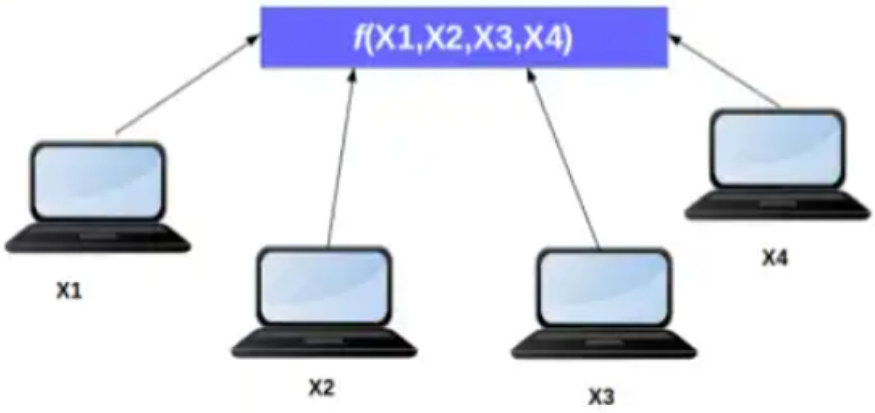

Figure 4: Secure Multiparty Computation

functions on the data by operating on the secret shares and can decrypt the final result by communicating the resulting shares amongst each other.

Secret sharing based protocols are popular techniques to achieve secure multi-party computation. In our project, we explore and use the library, namely `Crypten` which is based on secret sharing protocols. In this section we talk about the various protocols used by these libraries.

Shamir's Secret Sharing

Let $x \in \mathbb{F}$ be a secret. Shamir's secret sharing ensures that any t out of n parties can recreate the original secret but $t-1$ parties cannot. The way this is done is by picking a random $t-1$ degree polynomial f such that $f(0) = x$. Then the secret share that is given to party p is $[x]_p = f(p)$, $p \in \{1, 2, \ldots, n\}$.

If t parties combine their shares then they can interpolate their shares and recreate x as

$$f(0) = x = \sum_{i=1}^{t} \lambda_{p_i} [x]_{p_i}$$

where λ_{p_i} are coefficients given by

$$\lambda_{p_i} = \frac{\prod_{j=1, j\neq i}^{t} (0 - p_j)}{\prod_{j=1, j\neq i}^{t} (p_i - p_j)}$$

BGW Protocol (MPyC)

`MPyC` uses the BGW protocol to enable n parties to jointly evaluate a publicly known function without revealing their respective inputs in a way that is secure against an honest majority Let the function to be evaluated be $g(x_1, x_2, \ldots, x_n)$ where x_p is ithe input of party p and the arithmetic circuit that evaluates g is known to all the parties. Shamir's secret sharing is used with $t = \lfloor (n-1)/2 \rfloor$ to create shares for encrypted values.

Each party p picks a random t degree polynomial f_p, where $f_p(0) = x_p$ and sends the shares $[x_p]_q = f_p(q)$ to all other parties q. Each party now has a vector of shares. The protocol defines how sharing works for addition gates, multiplication gates and multiplication-by-constant gates.

Addition Gates For an addition gate $c = a + b$, the arguments a and b are first shared using Shamir's scheme in a $(t + 1)$-out-of-n fashion. Thus, each party p has the shares $[a]_p$ and $[b]_p$ corresponding to polynomials f_a and f_b such that $[a]_p = f_a(p)$ and $[b]_p = f_b(p)$. Then each party individually calculates their share $[c]_p = [a]_p + [b]_p$. Each party now holds a point on the polynomial $f(x) = f_a(x) + f_b(x)$. Since this polynomial also has degree at most t and $f(0) = f_a(0) + f_b(0) = a + b = c$, these are valid shares of c. The multiplication-by-constant gate can be implemented similarly where each party locally multiplies their share by the constant.

Multiplication Gates Consider a multiplication gate $c = ab$ where the shares $\{[a]\}_{p=1}^{n}$ and $\{[b]\}_{p=1}^{n}$ are shared to all parties. The parties first locally multiply their shares of a and b to each get a point on the polynomial $q(x) = f_a(x) \cdot f_b(x)$. The resulting polynomial can be of degree atmost $2t$ so some extra steps are required to obtain a sharing of c with degree atmost q. To do this, it is important to note that $c = q(0)$ can be written as a linear combination of the party's shares as

$$q(0) = \sum_{i=1}^{2t+1} \lambda_{p_i} q(p_i)$$

where λ_{p_i} are the appropriate Lagrange coefficients.

The protocol then dictates that $2t+1$ parties generate a sharing of their values of $q(p)$. Each party can then locally compute their share $[q(0)]_p = \sum_{i=1}^{2t+1} \lambda_{p_i} [q(p_i)]_p$

Arithmetic Secret Sharing (Crypten)

`Crypten` uses pseudo-random zero share (PRZS) in order to share values. Let the value to be shared be x, such that $x \in \mathbb{Z}/Q\mathbb{Z}$ where $\mathbb{Z}/Q\mathbb{Z}$ is a ring with Q elements. Suppose we have to share the value x with $p \in \mathcal{P}$ parties. Let the shares of x be denoted by $\{[x]_p\}_{p \in \mathcal{P}}$, where $[x]_p$ denotes the share of party p.
So to share the value x, the parties first generate a pseudo-random zero share (PRZS), having $|\mathcal{P}|$ random numbers, by the property of PRZS these shares sum to zero. The party which owns x adds x to its share of PRZS and then discards x.
Now, to recover x, it is clear that $x = \sum_{p \in \mathcal{P}} [x]_p \mod Q$.

Beaver Triples (Crypten)

Beaver Triples is a secret sharing based method of multiplying two integers.
Let us assume we have multiply shares of two integers x and y. Let [x] denote the secret share of integer x. We have to compute [z] such that $z = xy$.
Suppose parties have a secret sharing of a random product: [a], [b], [c] such that $c = ab$.
So, now each party also has [x] and [y], the protocol is as follows:

- Each party computes $[x - a] = [x] - [a]$ and $[y - b] = [y] - [b]$ and publishes this result. This all the parties know $x - a$ and $y - b$ but as a and b are random integers they don't know x or y
- All parties compute $[z]$ as:

$$[z] = [c] + [x](y - b) + [y](x - a) - (x - a)(y - b)$$
$$\text{So, } z = c + x(y - b) + y(x - a) - (x - a)(y - b)$$
$$z = c + xy - xb + xy - ay - xy + ay + xb - ab = xy$$

So using a random multiplicative triple, we can secretly multiply two numbers. This random multiplicative triple can be generated by a Trusted third Party(TTP) or by Oblivious Transfer(OT). `Crypten` uses a TTP to do this currently but support for using OT instead is expected to arrive soon.

5 Answering queries by merging interpolated grids

Let $p_i(x, y)$ be the i^{th} server's predicted pollution value at grid location (x, y) and $\sigma_i(x, y)$ be its confidence at the same point. Before answering the client's query, the n servers must combine their predictions. Let $\hat{p}(x, y)$ and $\hat{\sigma}(x, y)$ be these aggregated values. We use inverse-variance weighting to estimate $\hat{p}$ and $\hat{\sigma}$ since this gives the least variance estimate among all weighted averages. These are evaluated as below.

$$\hat{p}(x,y) = \frac{\sum_i^n p_i(x,y)/\sigma_i(x,y)^2}{\sum_i^n 1/\sigma_i(x,y)^2} \qquad \hat{\sigma}^2(x,y) = \frac{1}{\sum_i^n 1/\sigma_i(x,y)^2}$$

To perform the above computation, each server distributes a secure share of their values to the other servers and then performs a sequence of secure arithmetic operations to obtain shares of the aggregated values, $\hat{p}$ and $\hat{\sigma}$. This ensures that the servers don't reveal any sensitive information.

After we have these merged grids, we can perform query operations on the same with the client as another party. The client first specifies a sub-grid which includes its query route. The client then securely provides a binary mask on this sub-grid which describes its route. This mask is the client's input in the query computation and the sub-grid with pollution values is the input of the servers. The queries may be finding the average and maximum pollution in query path or counting instances when pollution is greater than a threshold. The entire pipeline is shown in figure 5. How their queries are replied to is described in algorithm 4.1. The queries *min* and *range* can also be dealt with similarly. All values here are shared secrets with computation happening in parallel in all parties involved. As described in the protocols described earlier, some computations may also require communication between the parties. A restriction we face is that we cannot use conditionals as intermediate results are stored as shared secrets and cannot be decrypted by the parties to decide which branch to take.

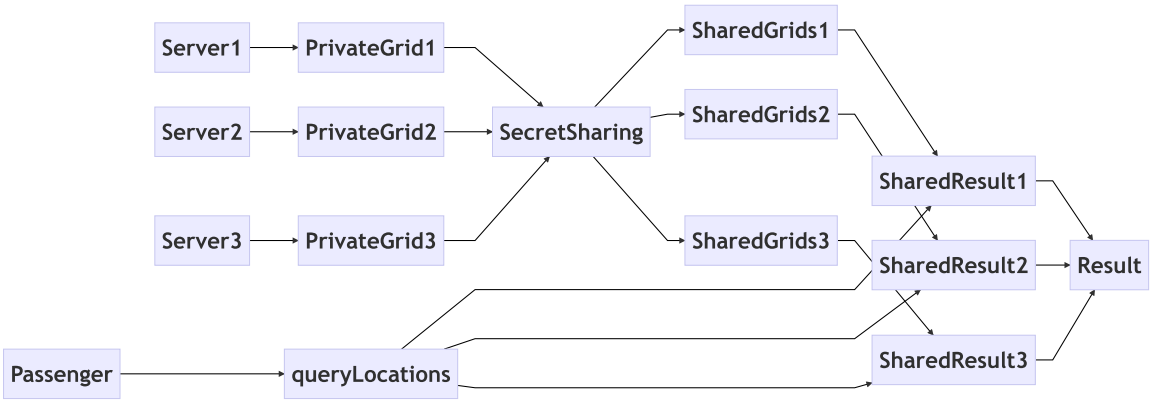

Figure 5: Query answering pipeline by merging interpolated grids

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Algorithm 5.1: REPLY$(query, \hat{p}, \hat{\sigma})$

$(sum, pathLength, sumVariance, max, count) \leftarrow (0, 0, 0, 0, 0)$

comment: average pollution along path

for each $(x, y) \in query.subgrid$

do $\begin{cases} onQueryPath \leftarrow query.mask(x, y) \\ sum \leftarrow sum + onQueryPath * \hat{p}(x, y) \\ sumVariance \leftarrow sumVariance + onQueryPath * \hat{\sigma}(x, y)^2 \\ pathLength \leftarrow pathLength + onQueryPath \end{cases}$

$avg \leftarrow sum/pathLength$

$avgConfidence \leftarrow \text{SQRT}(sumVariance)/pathLength$

comment: maximum pollution along path

for each $(x, y) \in query.subgrid$

do $\begin{cases} onQueryPath \leftarrow query.mask(x, y) \\ isGreaterThanMax \leftarrow \hat{p}(x, y) > max \\ max \leftarrow isGreaterThanMax * \hat{p}(x, y) + (1 - isGreaterThanMax) * max \end{cases}$

comment: count of points with pollution greater than threshold

for each $(x, y) \in query.subgrid$

do $\begin{cases} onQueryPath \leftarrow query.mask(x, y) \\ isGreaterThanThreshold \leftarrow \hat{p}(x, y) > query.threshold \\ count \leftarrow count + isGreaterThanThreshold \end{cases}$

return $(avg, avgConfidence, max, count)$

We use the secure MPC library, `Crypten` for the above setup. The different parties are simulated on a single machine using inter-process communication. The following sub-sections

discuss the key-points and results using library.

5.1 MPyC

Some important points about the `MPyC` library:

- It implements the BGW protocol.
- It is not suited for ML and gradient based learning.
- It is slow as the implementation is entirely in python and doesn't use any optimizations.

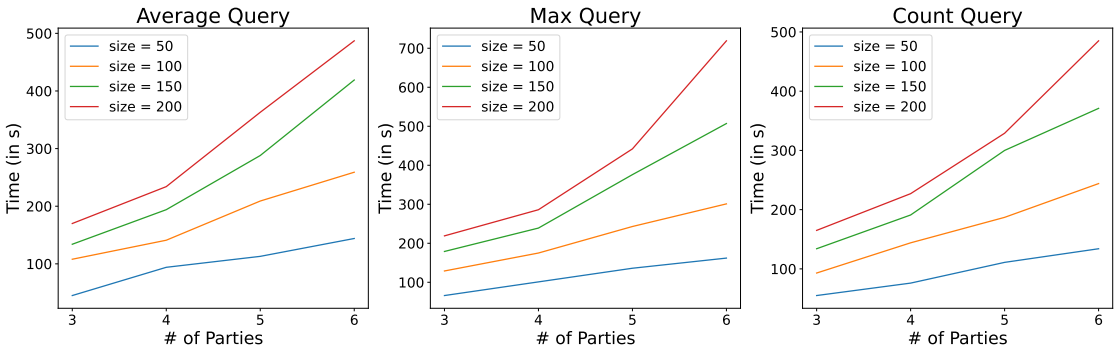


Figure 6: Timings of different queries with `MPyC`

Timing Results

As is expected, one can see the running time increase as the number of parties and the number of sub-grid points increase. Answering each query takes an order of a few minutes. We see that these running times are much slower that what we would need for real deployment as when run on multiple servers the timings would get much worse. The error in results generated by `MPyC` compared to a single process implementation were negligible.

5.2 CrypTen

`Crypten` is a Privacy Preserving Machine Learning framework written using PyTorch that allows researchers and developers to train models using encrypted data. `Crypten` currently supports Secure multi-party computation as its encryption mechanism where addition is carried out by simply asking the parties to sum their secret shares and multiplication using Beaver Triples. All linear functions are represented as a combination of addition and multiplication and all non-linear functions are implemented using standard approximations which use addition and multiplication. `Crypten` builds on pytorch and thus has a C++ implementation under the hood. It provides the following benefits to machine learning researchers.

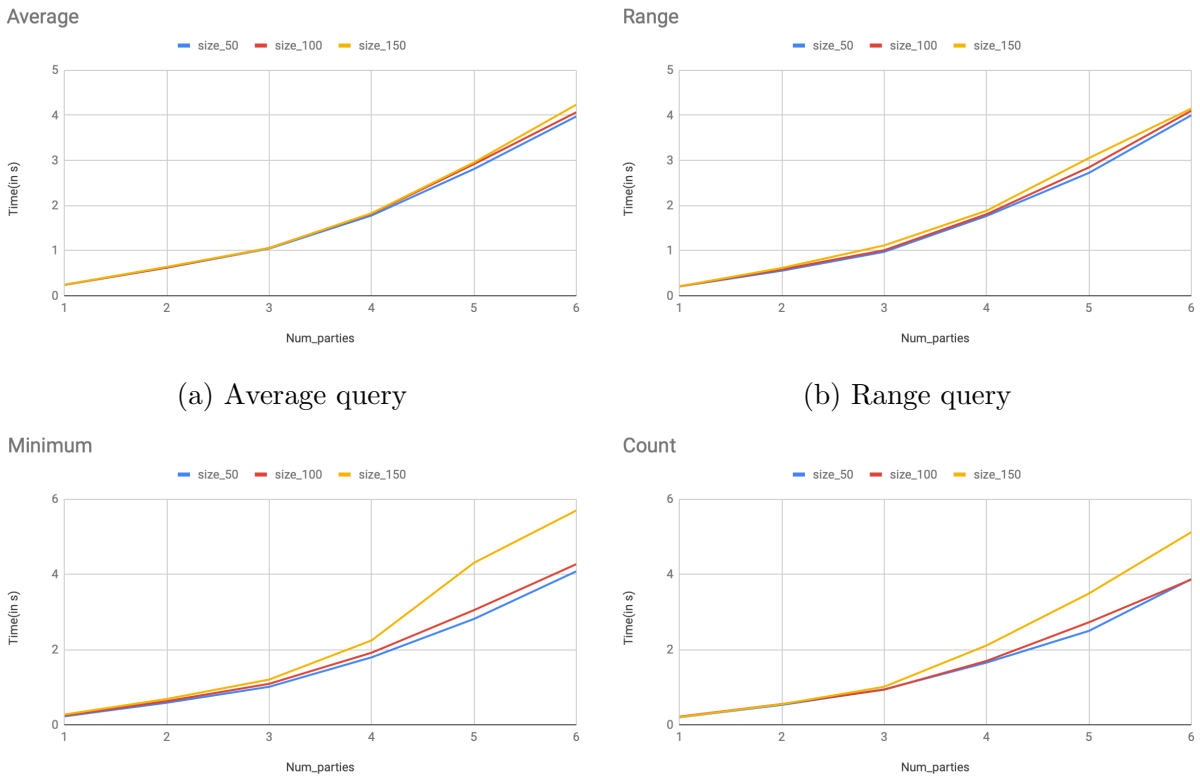
- The framework presents the protocols via a CrypTensor object that looks and feels exactly like a PyTorch Tensor. This allows the user to use automatic differentiation and neural network modules akin to those in PyTorch.

- `Crypten` is library-based. It implements a tensor library just as PyTorch does. This makes it easier for practitioners to debug, experiment on, and explore ML models.

- The framework is built with real-world challenges in mind. `Crypten` does not scale back or oversimplify the implementation of the secure protocols.

As a result, `Crypten's` performance is promising.

Timing Results



(a) Average query

(b) Range query

(c) Min/Max query

(d) Count query

Figure 7: Timings of different queries with `Crypten`

Note that the experiments here were run on a single machine. We observe that as the number of parties increase, the time taken also increases which is expected as communication costs increase. However, timing doesn't change a lot with increasing size. Also, `Crypten` provides a range of numbers on which some of the operators work accurately; out of that range we usually get junk values.

The errors increase very slightly as we increase the grid size. On average the relative error across different queries observed was:

Average: $10^{-3} - 10^{-4}$ %
Min/Max/Count/Range: $10^{-5} - 10^{-6}$ %

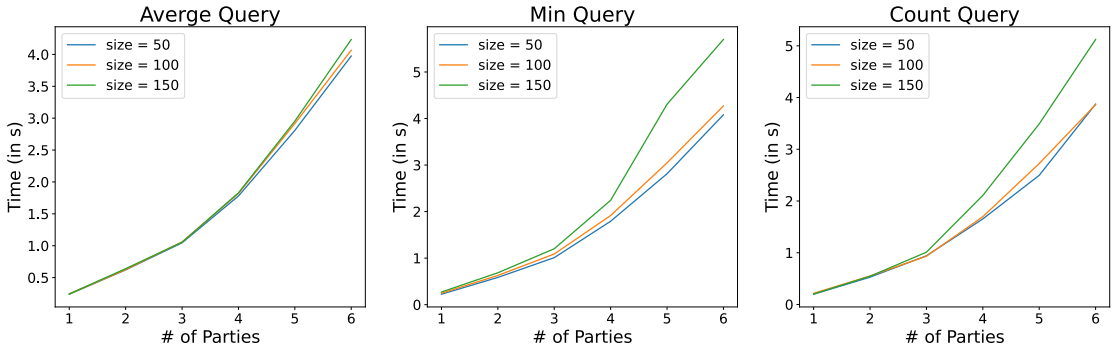


Figure 8: Timings of different queries with `Crypten`

6 Secure Interpolation across Servers

The pipeline discussed above where interpolation from different servers was used for answering queries is complete and can be used on it's own. However, there may be reasons to instead perform the interpolation together using data from all the servers. This can lead to better interpolation and take care of insufficient data at individual servers.

We explore two ways to achieve this — using Graph Convolution Networks and using Gaussian Process Interpolation. We discuss the results and issues with these in the following subsections. As before, note that interpolation needs to be done securely and the inputs and final interpolated values are all secure and shared. Also note that here the objective here isn't to get the best model to solve the problem but rather to understand how interpolation and learning can happen jointly across parties using available protocols and libraries.

6.1 Experiment setup

The city is divided into grids as earlier. The servers have their respective pollution values at different grid points. They secretly share these values and averaging is done on all known points. The above steps may be referred to as pre-processing. For the unknown points, we perform interpolation. We will like to point out that the data was relatively sparse with only values for $\sim 2\%$ grid points known in an hour.

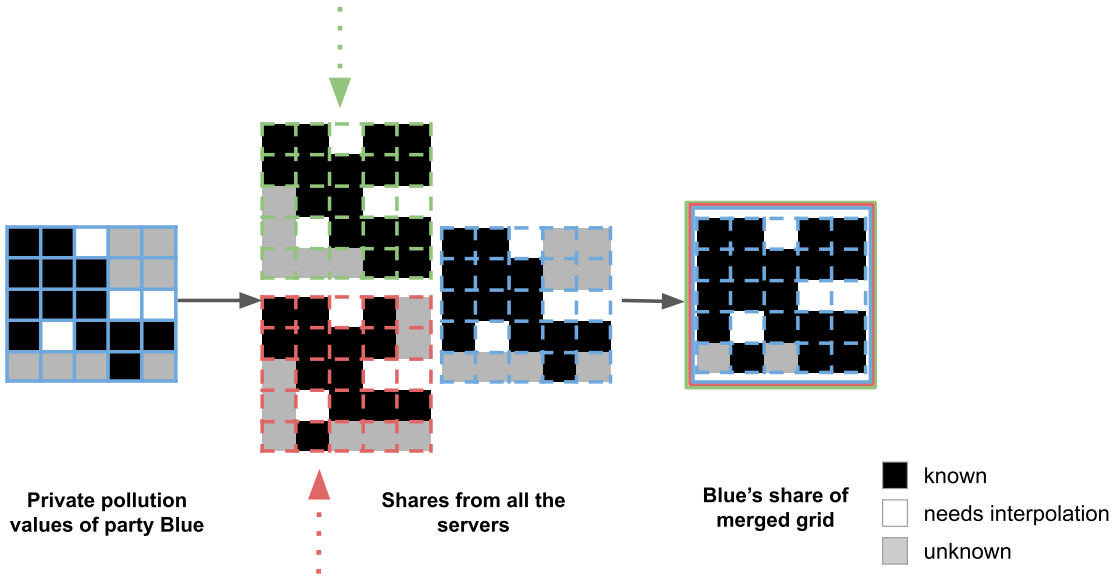


Figure 9: Preprocessing for Interpolation

6.2 Graph Convolution Networks

The input to a GCN is a graph and features of nodes of the graph. The output is the values of nodes which have to be predicted. This prediction is based on features of nodes and that of their neighbourhood. In our case, we take both the inputs and outputs to be pollution values with values of some location being unknown. We also take masks denoting whether values are known for grid points to be another set of input. This way, the unknown points can be predicted by using values of their neighbours. The Adjacency matrix is such that there are outgoing edges only from nodes whose values are known.

To perform interpolation we use the GCN model. The GCN architecture involves two graph convolution layers followed by a fully connected layer. The input graph has edges between adjacent grid points. The model is trained on data accumulated in an hour. The weights learned however can be reused as pre-trained weights in later time windows. The input is split to test and train sets, with 1/20 of the locations being test locations. Some of the train points are randomly masked while training so that the model learns to predict values for unknown locations.

The training happens securely between parties so that the model learned is shared between them. Finally, predictions are made on the test points with the result for the entire grid now stored securely in a shared way between all the parties.

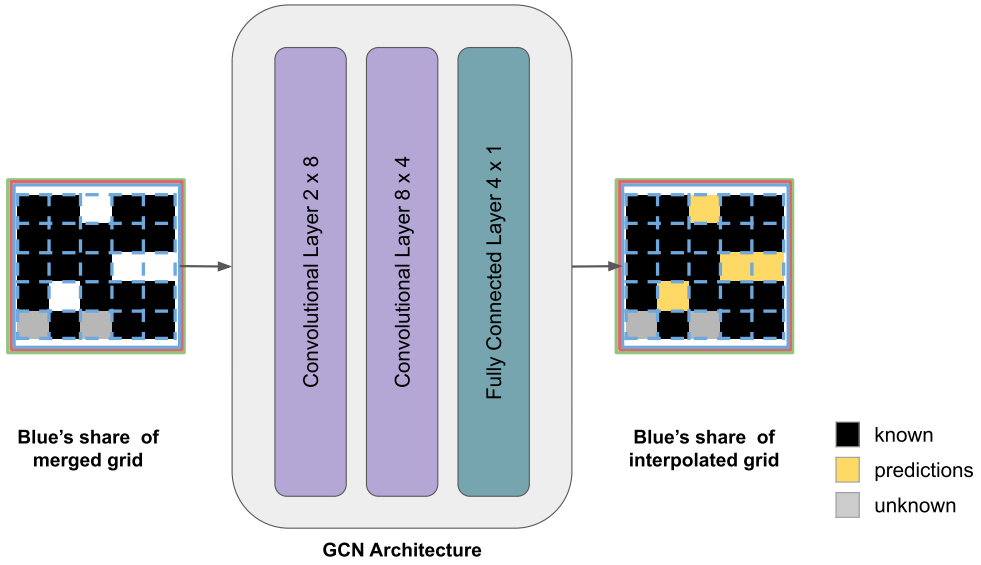
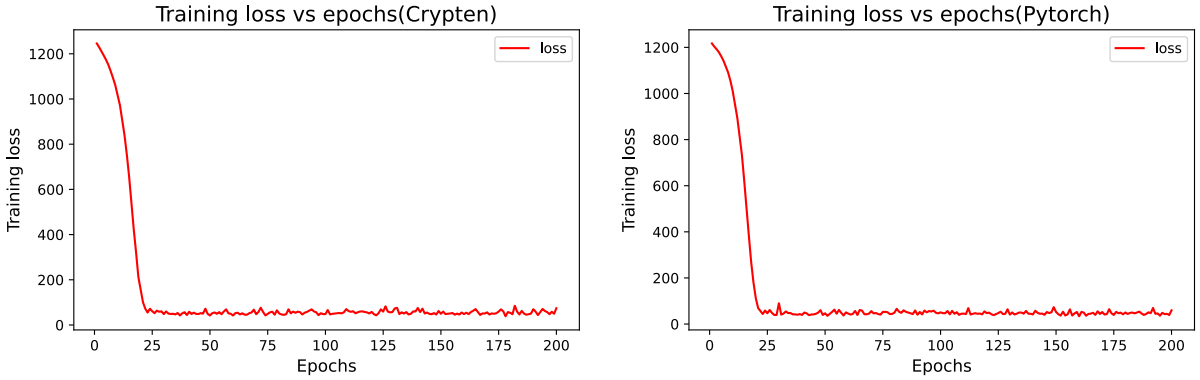


Figure 10: GCN Interpolation

Note that the experiments here were run on a single machine with all inter-party communications happening as inter-process communications. We use the `Crypten` library to achieve secure computation. We also implement the same pipeline (modulo shared secrets) using `Pytorch` and compare the results obtained.

6.2.1 Results

Training While training, `Crypten` performed as good as the standard `Pytorch` implementation when using SGD (Stochastic Gradient Descent), as evident from Figure 11.

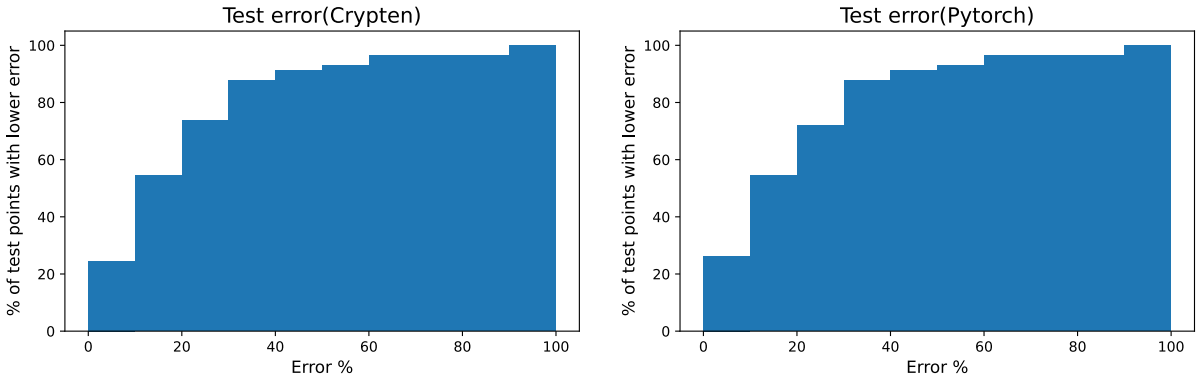


(a) Crypten (b) Pytorch

Figure 11: Training loss vs epoch

Accuracy The histograms in Figure 18 show the what % of test points have how much error. In this histogram, as well we can see performance of `Crypten` and vanilla `Pytorch` is similar. This error % is for 4 different hours of data, for each hour model was first trained for 200 epochs and then tested. For both, `Crypten` and vanilla `Pytorch`, around 75% of the points have error

less than 30%. Also, the points on which both of them performed poorly were usually the ones which had no known neighbors or differed significantly from their neighbors.



(a) Crypten (b) Pytorch

Figure 12: Error %

Timing and Communication In terms of time, on the same machine `Crypten` is almost 100 times slower than `Pytorch`. For communication v/s computation breakup of `Crypten` we will analyse two stages of training separately, the two stages are:

1. **Pre-processing**: In this part the parties transfer the secret share of their data to each other and aggregate all the shares available to them before training.

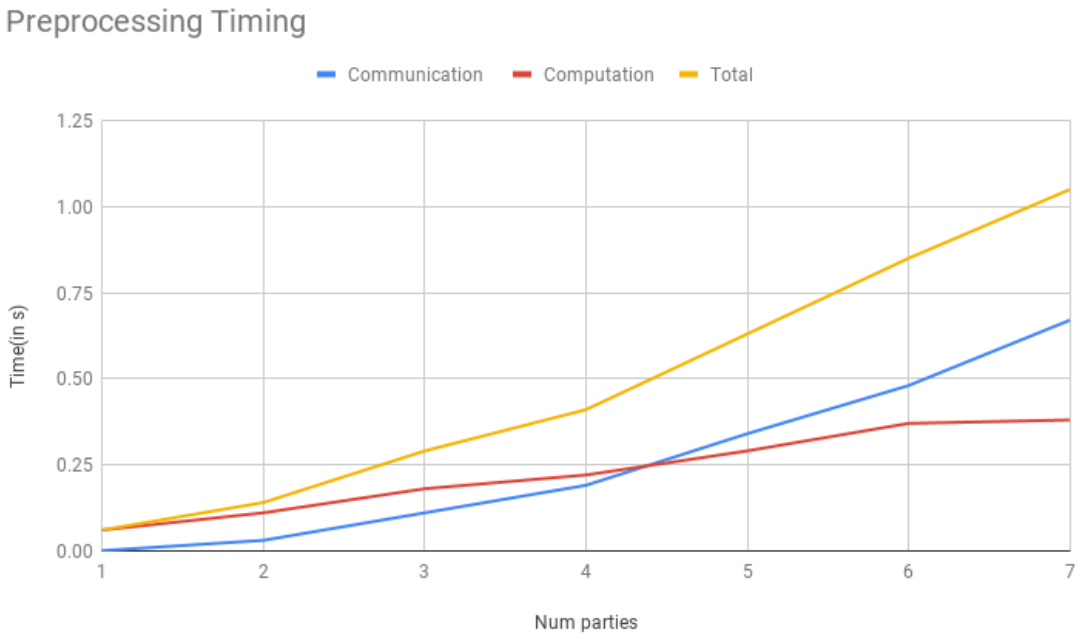


Figure 13: Preprocessing Timing

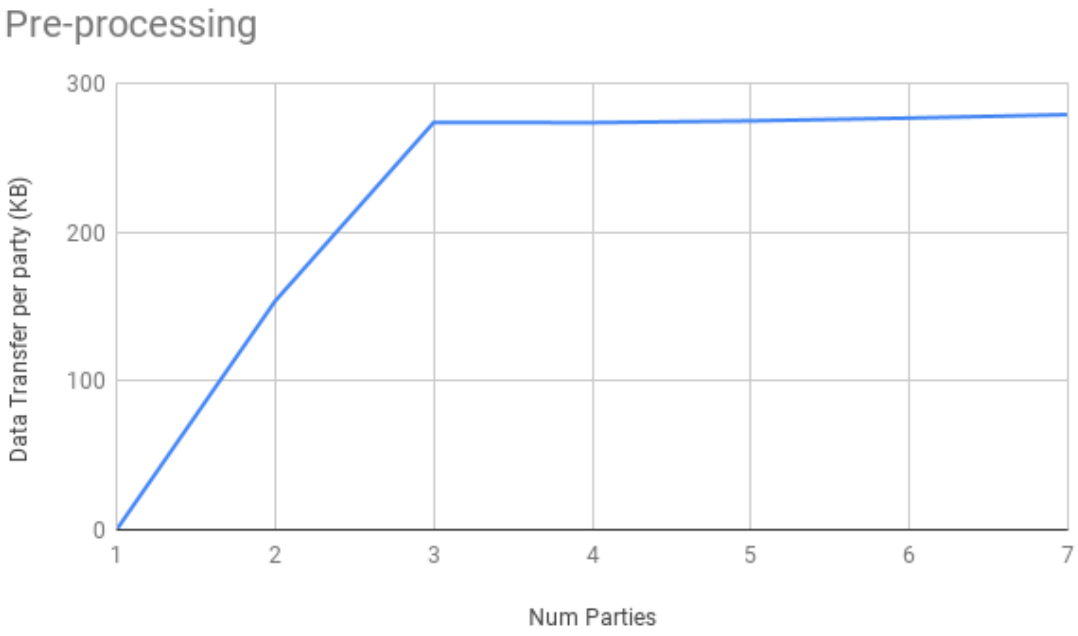


Figure 14: Preprocessing data transfer

It is evident from the figure 15 that as we increase the number of parties, the communication time starts to dominate which is as expected. However, we see that the computation cost also increases slightly, this is because as the number of parties increases more grids have to be aggregated.

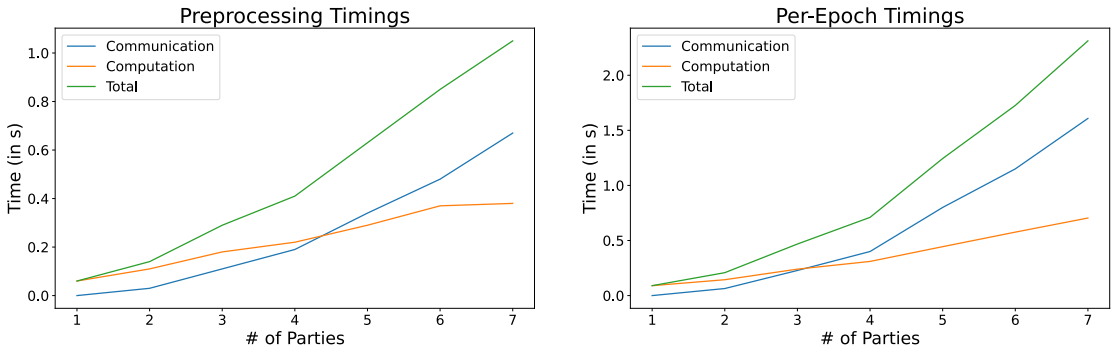


Figure 15: Timings during training the model in `Crypten`

2. **Training**: In the training phase, each party trains their own Graph Convolution Network for interpolation.

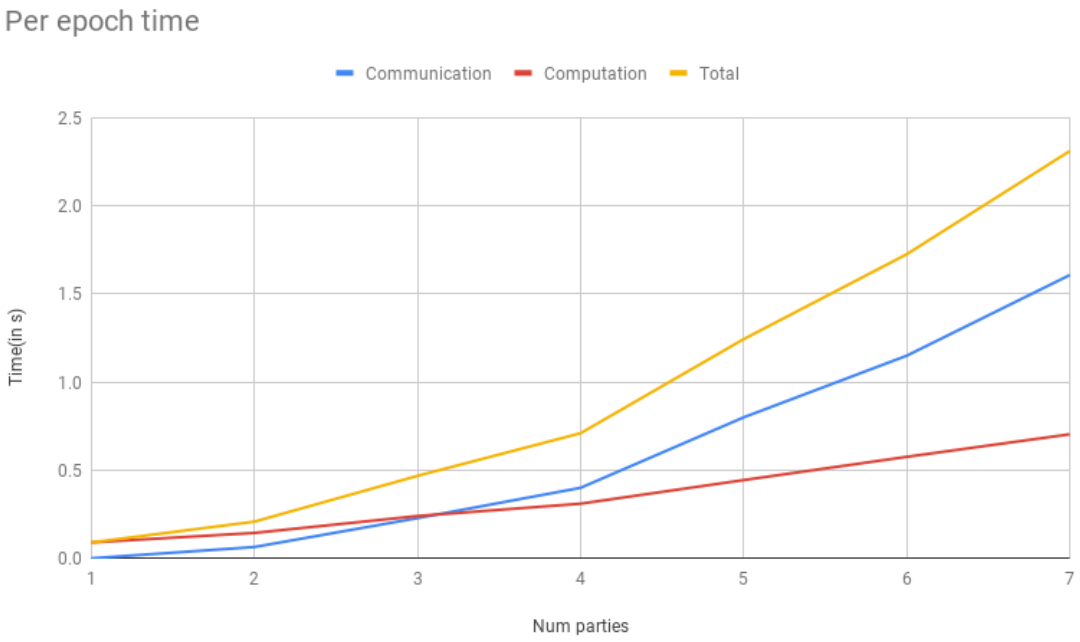


Figure 16: Per epoch time(Average over 5 epochs)

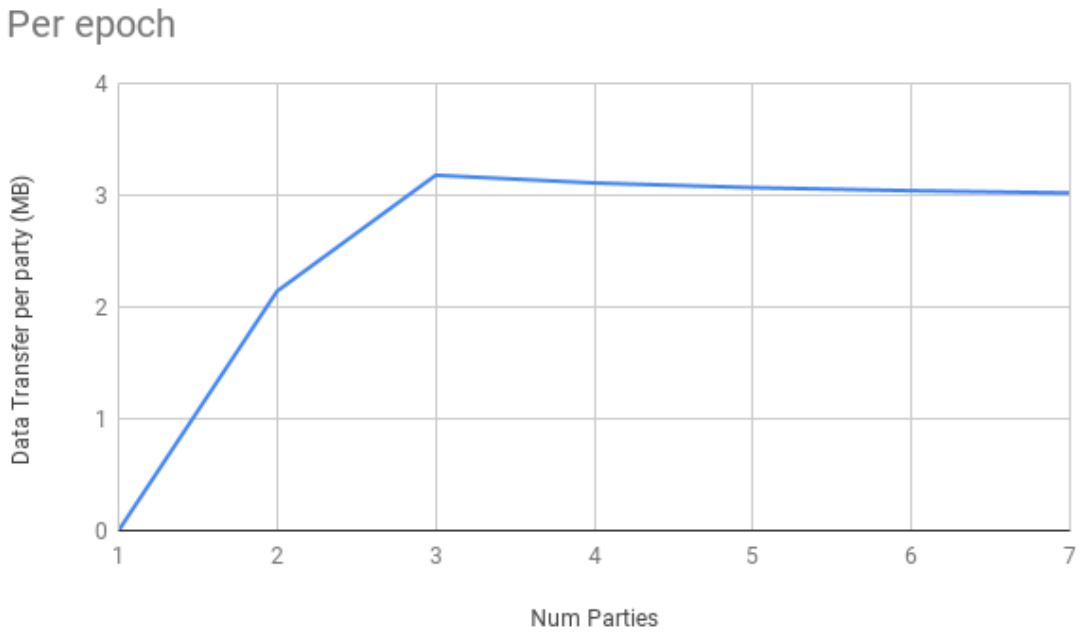


Figure 17: Per epoch data transfer(Average over 5 epochs)

Here also, from Figure 15, we observe as the number of parties increase, the communication time starts to dominate. In per epoch timing, this effect is seen earlier as compared to in

pre-processing, this is because in pre-processing there is significant CPU computation at each server as well.

6.2.2 Issues faced while using GCN

Some issues we faced by using GCN for interpolation were:

- GCN doesn't return a confidence score.
- The test points need to be neighbours of known points.
- `CrypTen` doesn't support Adam optimizer which gave better results when the model was implemented in `PyTorch`.
- There were very few train points after we divide the city up into grids.

6.3 Gaussian Process

Definition: *A Gaussian process is a collection of random variables, any finite number of which have a joint Gaussian distribution.*

A Gaussian process is completely specified by its mean function and covariance function. We define mean function $m(x)$ and the covariance function mean function $k(x, x')$ of a real process f(x) as

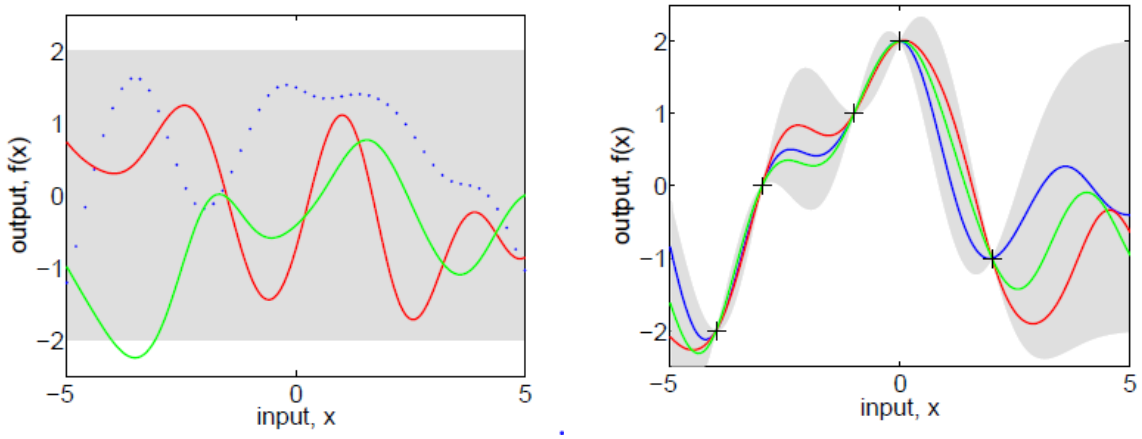
$$m(x) = E[f(x)]$$

,

$$k(x, x') = E[(f(x) - m(x))(f(x') - m(x'))]$$

, and will write the Gaussian process as

$$f(x) \sim GP(m(x), k(x, x'))$$



(a) prior (b) posterior

Figure 18: (a) shows three functions drawn at random from a GP prior; (b) shows three random functions drawn from the posterior, i.e. the prior conditioned on the five noise free observations. In both plots the shaded area represents the pointwise mean plus and minus two times the standard deviation for each input value (corresponding to the 95% confidence region), for the prior and posterior respectively.

We are usually not primarily interested in drawing random functions from the prior, but want to incorporate the knowledge that the training data provides about the function. To get the posterior distribution over functions we need to restrict this joint prior distribution to contain only those functions which agree with the observed data points and rejecting the ones that disagree with the observations. Complexity of model posterior can grow as more data are added.

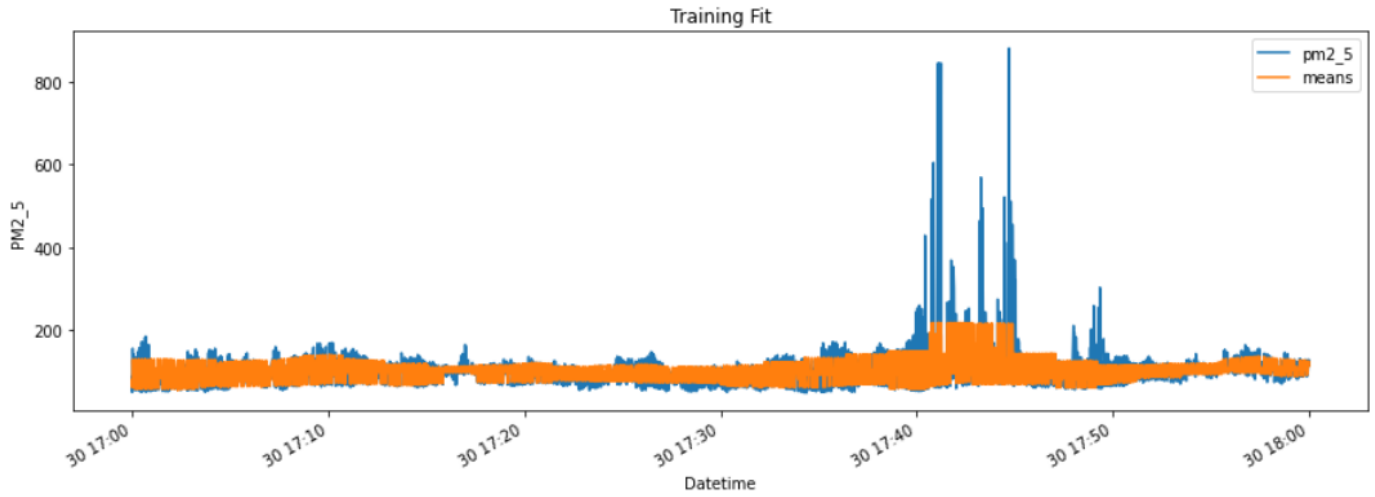


Figure 19: Training fit for Gaussian Process on Pollution Dataset

Gaussian Process Regression

Gaussian Process Regression(GPR) is a non-parametric Bayesian regression approach which uses sampled measurement (training) data to provide interpolation estimates. For a known training input-output pair (X; y), GPR predicts the values of the underlying latent (unobserved) function, f*. This generates the test output, y*, on the set of input testpoints, X*.

6.3.1 Advantages of using GP over GCN

Some of the advantages of using Gaussian Process interpolation over Graph Convolutional Network interpolation are:

- The predictions are probabilistic (Gaussian) so that one can compute empirical confidence intervals and estimate uncertainty in the predictions.
- Unlike GCN, Gaussian Process regression allows to make predictions on continuous input locations
- It also provide a convenient language for expressing domain knowledge. Common knowledge is expressed through priors and different choice of kernels. Prior is specified over function space and intuitions are likely to be stronger in function space. e.g., smoothness constraints on function, trends over time, etc.
- In the problems with limited data, the data themselves aren't sufficient to constrain the model predictions. Gaussian processes place a prior over functions directly rather than over model parameters.

6.3.2 Library used for GP - gpytorch

We explored different GP libraries and analysed how their code base can be ported to `Crypten`. The key takeaways while trying to port different GP libraries to `Crypten` were that libraries should be based on PyTorch to port to `Crypten`. We observed that large libraries like gpytorch have very large number of lines of code with specific classes like LazyTensors defined on top of PyTorch which are not easy to port to `Crypten`. Other smaller libraries like gptorch and pyro did not give very accurate and reliable results even in a non-MPC setting. So, we mostly focused on and studied gpytorch for porting `Crypten` to GP.

GPyTorch is a Gaussian process library implemented using PyTorch. GPyTorch is designed for creating scalable, flexible, and modular Gaussian process models with ease.

6.3.3 Challenges while deploying `Crypten` on gpytorch

Gpytorch is a very large GP library implemented on Pytorch and deploying `Crypten` on gpytorch is not a trivial task, indeed a challeging one. Some of the challenged we are facing are:

- gpytorch converts Pytorch tensor to LazyTensor for kernel and covariance matrix calculations which is not supported on `Crypten` tensor.
- Certain bool comparisons in gpytorch are not compatible with MPC Tensor because `Crypten` doesn't support bool operations without converting it into plaintext.
- GP uses a special Variational ELBO loss function from gpytorch library which is not supported by `Crypten`. `Crypten` currently supports very limited set of loss functions.

7 Road Map Ahead

Currently, we are exploring the ease and usage of secure MPC library Crypten and trying to port Crypten in Gaussian Process for performing the inerpolation task. We are currently facing several challenges in this deployment of Crypten to GP as mentioned above. Crypten's framework needs significant coding efforts as Crypten currently supports few ML functions that need to be extended. The next task is to develop a working library for GP ported with Crypten for secure computations of interpolation on grid points. Next, we will analyze the accuracy-vs-latency trade-offs of our implementation, as pollution is a dynamically changing phenomena, and the interpolation has to run periodically, instead of a single shot ML model training. Thus latency of model training using Crypten is important. Based on the trade-off analysis of whether computation in the cryptographic protocol is the bottleneck or communication among the different fleet companies' servers holding the data, we will try appropriate optimizations. The work will this involve understanding of cryptographic protocols, ML and systems.

References

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