National College of Ireland

Multi-Tenant Data Filtering in Fog Nodes for Privacy-Preserving IoT Data Processing

MSc Research Project
Cloud Computing

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MSc Project Submission Sheet

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Multi-Tenant Data Filtering in Fog Nodes for Privacy-Preserving IoT Data Processing

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https://github.com/x23267062/IOT_sim.git

Abstract

The IoT devices that flourish in the 5G multi-tenant settings contributed to the increased demand of privacy-preserving data processing at the edge where sensitive data (e.g. user IDs, locations) is produced. The conventional cloud-dependent strategy causes a problem with bandwidth, latency, and increased security vulnerabilities, which calls for the localized computing approach which is fog computing. The proposed research will focus on the essential issue of ensuring privacy, security and efficiency in multi-tenant IoT data processing. The developed simulation tool was then deployed to run on AWS Elastic Beanstalk offering synthetic IoT datasets to three tenants more than 30 seconds in run time and functions using a Flask framework. The framework operates cryptpandas in anonymizing sensitive data, partitioning them into encrypted .crypt files and non-sensitive .csv files and assessing the performance outcomes based on psutil and Matplotlib representations, which are utilized in Amazon S3. The results of the experiment clearly show that the utilization of the approach has resulted in the decreased execution time (55 ms to 40 ms) and memory usage (60 MB to 45 MB) and in essentially zero data utility lost (<1%), which confirms the effectiveness of the approach. The research is a gap filler in already existing literature as it provides scalable GDPR-compliant model that opens the doors to edge-based IoT solutions.

1 Introduction

1.1 Background

Rapid data growth assuming the presence of IoT devices in 5G networks, particularly in multi-tenant environment, implies that many parties or users are sharing network resources. The issue with this increase of interest in the field of fog computing and network security is the privacy of the sensitive data that is generated by devices connected to the IoT systems, which may include identifiers, locations, and other relevant information being one of the primary tasks to protect it, at-the-edge of 5G networks, where the data is initially gathered. In the traditional models, it is assumed that all the data will be transferred to cloud servers to be processed. This is not normally justified and causes unnecessary use of bandwidth, processing delays, and vulnerability to security attacks. The use of multi-tenant systems, like in the case of 5G, poses threats since there is no strong means of maximum privacy and a segregation of tenants, which work powerfully against information protection and operational efficiencies given that such a form of 5G is characterised by convergence of data with various sources. Incorporation of IoT in each of the sector including smart cities, healthcare,

industrial application, etc, involves manipulation of sensitive information and even a single breach might result to humongous damages or violation of law like the General Data Protection Regulation (GDPR). Furthermore, relying on the cloud to process appears to be directly contradicting the full momentum of 5G: Low latency and scalable leading to network bottlenecks. Multi-tenant 5G would have numerous solutions, which are needed to guarantee data safety starting at its source. Literature is in a very poor state in regards to these issues. Theodorou and Xezonaki (2020)[15] have an interesting report on edge processing in multi-tenant environment but did not include privacy. Without arguing or focusing on the emphasis on privacy at the age level, Escolar et al. (2021)[6] enhance the 5G network slicing to ensure the best use of resources. Beeruka (2023)[1] goes further to push data anonymization in clouds; an approach that is considerably out of the scope of the demands of 5G edge.

1.2 Motivation

The growth of the IoT ecosystems increase the desire to use local processing because the amount of data collected and its diversity are large, and they include personal health indicators and industrial telemetry. Fog computing seems to be feasible, with computation assets being near data generation; nevertheless, the application of fog computing in the context of privacy insuring on multi-tenant 5G is scarcely studied. The cloud-centric paradigm, thus, refutes the idea that the risks can be diminished by the fog nodes prior to data exiting the edge, which leads to identifying the research direction that requires urgent investigation.

1.3 Describe variables or factors that affect the outcome

How network resources will be assigned without necessarily addressing the privacy concerns in the edge, where IoT devices will finally have access to the network is largely the evolution of 5G with its promises of improved connectivity through network slicing, where the network is sliced into virtual slices based on such requirements as massive IoT or ultralow latency applications.

Research question - How can multi-tenant IoT data processing be effectively simulated to enhance privacy, security, and efficiency while optimizing execution time and memory usage?

1.4 Research objective

- Investigate the state of the art broadly around privacy-preserving techniques in fog computing and 5G multi-tenant environments.
- Design a filtering framework for fog nodes in 5G networks.
- Implement the framework deployed at fog nodes, integrating real-time IoT data streams.
- Evaluate the framework's performance against raw data filtering based on execution time, and memory usage.

1.5 Contribution

This study has a number of contributions. It enhances privacy in the aspect that delicate data is computed by fog nodes hence complying with the terms and conditions of GDPR and safeguarding individuals in a multi-tenant environment of 5G. It reduces the processing on

the cloud thus enhancing the use of bandwidth consequently resulting in a far superior efficiency and scalability. It also forms a replicable framework of deploying multi-tenant IoT systems in 5G networks which has implication signatures on the transformation of security on edge computing.

Report Structure:

Section	Title	Description
1	Introduction	Introduces privacy-performance challenges in multi-tenant IoT, stating research question, objectives, and contributions.
2	Related work	Reviews privacy and performance techniques in IoT, identifying gaps in multi-tenant data processing.
3	Research Methodology	Details simulation framework with cryptpandas anonymization, Elastic Beanstalk deployment, and metrics (execution time, memory usage).
4	Design Specification	Data flows from generation to anonymization, processing, and visualization.
5	Implementation	Generates synthetic IoT datasets for three tenants.
6	Evaluation	Compares simulation performance against raw and anonymized methods, assessing execution time, memory, and data utility.
7	Ethical and Timeline Considerations	Addresses GDPR compliance and data ethics, with a timeline of key milestones for development and testing.

2 Related Work

The knowledge of data anonymization, removal of sensitive data, and monitoring is essential for the creation of an efficient and secure system of data processing in IoT. This discussion looks at other research articles to guide in the design of a proposed simulation framework using reputable sources that discuss legal guidelines, anonymization techniques, tools and their uses in multi-tenanted IoT image.

2.1 Anonymization Techniques and Privacy Preservation

Multiple research works have been carried out on the topic of data anonymization to strengthen privacy of IoT and other fields. Tarini Beeruka (2023)[2] demonstrates one of the simulations with a medical dataset in Kaggle, CryptPandas, and Amazon S3, it contributes 45.5 percent faster execution, 33.3 percent less consumption of memory without losing the accuracy, but it is aimed at the medical field and can hardly be applied to more general IoT applications, so there is also a step in connecting to multi-tenant, real-time data processing. The experiment by Chunchun Ni et al. (2022)[8] focuses on anonymization algorithms on UCI datasets, paying attention to the privacy-utility trade-offs but cannot be seen to be an edge-focused solution because of its data limitations. Ajmeera Kiran & N. Shirisha (2022)[7] report 83-86 percent accuracy with K-anonymization on the Adult dataset under WEKA, but

their algorithm-specific design, as well as the lack of 5G context, make it possible to conduct research on IoT scale rather than on algorithms. Representations in these works have generally demonstrated the potential of anonymization but have shown a vulnerability to periods of multi-tenant interactions and fast-moving situations.

2.2 Security and Filtering in Fog and 5G Environments

Other context is offered in terms of research on security and filtering. Gowtham S et al. (2023)[21] introduce a fog computing simulation with three algorithms, which involve balancing privacy and costs with AES encryption, which is however a limitation given the absence of multi-tenant support and focus on latency, therefore they recommend an integration with 5G in the future. According to a survey of wireless technologies related to IoT security by L.P. Rachakonda et al. (2024)[11], spectrum sharing contributes to security, but the lack of validation of the approach is viewed as a weak point, and edge-specific ciphers are not developed yet. Devasis Pradhan et al. also (2024)[9] provide a qualitative assessment of the security of 5G-IoT in smart cities, with some protocol recommendations but no experimentation, emphasizing the need to conduct real-time studies of mitigation. Zakaria Benomar et al. (2019)[20] support fog with OpenStack containers and meet the goal of low latency at a single device, but their scalability in different IoT devices is still to be seen. These papers are excellent reinforcements of the argument of security using fog although they do not have complete multi-tenant and performance optimization.

2.3 Network Slicing and Multi-Tenancy in 5G/6G

The research of network slicing can provide insight into multi-tenancy. Chirivella-Perez et al. (2023)[4] automate 5G E2E slicing using Java/Python, deploying NSIs in less than 0.5 s on 512 machines; it performs well in scale but poorly in security, because privacy is not integrated, indicating an opportunity to use edge security in future research. A. Matencio Escolar et al. (2021)[6] scale 5G IoT slicing using OpenSliceVS, which supports 1M devices, and achieves an edge-to-edge 133 Vasileios Theodorou et al. (2020)[15] manage to isolate tenants using EdgeX Foundry, which instantiates within 258s, whereas small-scale testing and throughput silos suggest that stress-testing is warranted. By optimization of 6G E2E slicing using DRL improve the accuracy of the affiliation but the absence of user equipment and a focus on non-virtualization should be addressed in future by integration with LLM. These articles draw our attention to the multi-tenancy capability of slicing but fail to demonstrate privacy-performance synergy.

2.4 Performance and Simulation Frameworks

The aspect of simulation is informed by performance-centered investigations. Vasileios Theodorou et al. (2020)[15] and Zakaria Benomar et al. (2019)[20] offer viable fog and slicing prototypes, and they excel in areas of low-latency and containerization, however, they lack scalability learnings due to small size. The simulation-based improvements presented by Tarini Beeruka (2023)[2] and Chunchun Ni et al. (2022)[8] require generalization of the IoT applications because of limited dataset and restricted focus on the edge. This represents an important gap between these studies since integrated multi-tenant performance parameters are lacking.

2.5 Summary and Justification

The provided review of the literature unveils that there is a strong background in the field of anonymization (Beeruka, 2023; Ni et al., 2022)[2], fog security (Gowtham et al., 2023; Pradhan et al., 2024)[9][21], and 5G slicing (Chirivella-Perez et al., 2023; Escolar et al.,

2021)[4][6], but the proposed solutions cannot be used in the context of the multi-tenant IoT data processing, real Current literature does not elaborate simulation frameworks that are unified with edge/fog computing, scalable anonymization, and more granular performance data (e.g., time of execution, memory utilization) or which are implemented in a multi-tenant scenario. This gap informs the relevance of the proposed research question; that is, how should multi-tenant IoT data processing effectively be simulated to improve privacy, security, and efficiency with a view to optimizing the execution times and memory consumption? The suggested framework of the simulation on the basis of Flask, which utilizes cryptpandas and Elastic Beanstalk, is meant to address these gaps, as it can provide a scaled, privacy-preserving model with real-time examinations in the performance.

In order to find out how to implement fast and secure IoT data processing systems, it is useful to understand three things: the meaning of the term data anonymization, how to eliminate sensitive information, and how to measure performance. The approach is to review those studies that are applicable to the given study and the characteristics such as guidelines on legality according to the law, anonymization procedures, type of tools and the importance of their usage. It is also able to draw inspiration with the credible sources who inform the establishment of the proposed simulation framework.

Table 1.Comparison of Related Works

Author/Source Title/Year	**Purpose/Rationale/Aims/Question posed**	**Method/sample characteristics/study type**	**Results/findings/conclusions**	**Key ideas/themes**	**Strength/weaknesses/limitations/gaps – areas for further research**	**Similarities/differences to other studies**	**Notes/my conclusions/comments/questions arising**
Tarini Beeruka (2023) – "Effective Anonymization"	Enhance privacy with optimal anonymization, asking: How to maximize privacy with minimal loss?	Simulation with Kaggle Medical dataset, CryptPandas, Amazon S3	45.5% faster execution, 33.3% less memory, no accuracy loss	Anonymization; Privacy; Cloud computing	Strength: Efficient; Weakness: Medical-only; Gap: No 5G/latency; Research: Multi-tenant, real-time	Similar: Gowtham (encryption); Diff: Cloud vs Fog	Relevant for fog filtering; Question: 5G latency impact?

Gowtham S et al. (2023) – "Multi Access Filtering"	Reduce privacy leaks in fog, asking: How to enhance privacy with filtering?	Simulation with IoT data, three algorithms (tuple reduction, etc.)	FAF balances privacy/costs with AES encryption	Fog computing; Filtering; Privacy	Strength: Encryption; Weakness: No multi-tenant; Gap: Latency; Research: 5G integration	Similar: Wang (security); Diff: Fog vs Cloud	Relevant; Question: 5G multi-tenant latency?
Chirivella-Perez et al. (2023) – "E2E Network Slice"	Automate E2E 5G slicing for QoS, asking: How to manage slices efficiently?	Empirical with Java/Python/C, 512 machines, OpenStack	<0.5s NSI deployment, E2E slicing, mobility	Automation; Multi-tenancy; QoS	Strength: Scalable; Weakness: No privacy; Gap: Edge security; Research: IoT privacy	Similar: Escolar (QoS); Diff: Network vs Data	Complements 5G filtering; Question: NSTs for policies?
Ajmeera Kiran & N. Shirisha (2022) – "K-Anonymization"	Preserve privacy with K-anonymization, asking: How to minimize data loss?	Empirical with WEKA, Adult dataset, Z-score, Naive Bayes	83-86% accuracy with minimal loss	K-Anonymization; Perturbation; Privacy	Strength: Accurate; Weakness: Algorithm-limited; Gap: No 5G; Research: IoT scalability	Similar: Data mining studies; Diff: No network focus	Aligns with privacy; Question: IoT stream fit?
L.P. Rachakonda et al. (2024) – "IoT Privacy/Security"	Optimize spectrum for IoT security, asking: How to address privacy via sharing?	Survey on wireless tech, IoT applications	Spectrum key, security risks noted	Spectrum sharing; IoT Security; 5G/6G	Strength: Broad; Weakness: No validation; Gap: Edge/6G; Research: Multi-attribute security	Similar: K-anonymization; Diff: Spectrum focus	Aligns with edge filtering; Question: Edge cryptography?
Devasis Pradhan et al. (2024) – "IoT Security 5G"	Secure 5G-IoT in smart cities, asking:	Qualitative survey on 5G, IoT, security	Highlights risks, suggests protocols	5G; IoT Security; Smart	Strength: Overview; Weakness: No testing;	Similar: Rachakonda; Diff:	Relevant for edge; Question: Edge protocol latency?

	How to mitigate threats?	protocols		cities	Gap: Edge/6G; Research: Real-time mitigation	Smart city focus	
A. Matencio Escolar et al. (2021) – "Adaptive Slicing"	Scale 5G IoT slicing, asking: How to manage heterogeneous traffic?	Empirical with OpenSliceVS, 2-node NUMA, 3 VMs	1M devices, 0% loss, 133 µs latency	Slicing; SDN; Multi-tenancy; QoS	Strength: Scalable; Weakness: No privacy; Gap: Edge; Research: Privacy integration	Similar: Chirivella; Diff: Network vs Privacy	Relevant; Question: Privacy with OpenSliceVS?
Chunchun Ni et al. (2022) – "Data Anonymization"	Evaluate anonymization for IoT, asking: How to balance privacy/utility?	Experimental with UCI datasets, five algorithms	Trade-offs in privacy/utility noted	Anonymization; IoT Privacy; Algorithms	Strength: Comprehensive; Weakness: Dataset-limited; Gap: Edge; Research: Fog integration	Similar: Beeruka; Diff: Evaluation vs Slicing	Relevant; Question: Fog node latency?
Zakaria Benomar et al. (2019) – "Container-based Fog"	Enable fog with OpenStack, asking: How to manage edge containers?	Experimental with Zun/Kuryr on Orange Pi0	Low-latency, 0-4 Mbps throughput	Fog; IoT; Containerization	Strength: Practical; Weakness: Single-device; Gap: Scalability; Research: Diverse devices	Similar: Distefano; Diff: Infrastructure vs Data	Relevant for 5G; Question: Scalability across IoT?
Vasileios Theodorou et al. (2020) – "Network Slicing"	Share IoT via 5G slicing, asking: How to support multi-tenancy?	Experimental with EdgeX Foundry, OSM, two VMs	258s instantiation, tenant isolation	Slicing; Multi-tenancy; Edge	Strength: Prototype; Weakness: Small-scale; Gap: Throughput; Research: Stress-testing	Similar: Benomar; Diff: Slicing vs Containers	Relevant; Question: Isolation under load?
Sina Ebrahimi et al. (2024) –	Optimize E2E 6G NS, asking:	Review with testbeds,	E2E improves accuracy,	Network Slicing;	Strength: Broad; Weakness:	Similar: Wu; Diff:	Critical for 6G; Question: LLM in orchestration?

"6G Network Slicing"	How to manage resources?	276 studies	DRL key	6G; DRL; Security	No UE; Gap: Non-virtualized; Research: LLM integration	E2E vs RAN	

2.6 Legalization and GDPR

The European Union has established General Data Protection Regulation (GDPR) assessing the terms according to which companies need to collect, manipulate and maintain personal data to keep it safe. Personal data is used to refer to all information that helps to identity a person, directly or indirectly, including names, phone numbers, addresses, and even concluded information based on their health or web habits (Voigt and Von dem Bussche, 2017)[18]. Because IoT systems continuously produce data, GDPR compliance is essential to prevent the violation of user privacy. Products Spoofing The information that can be identified is electronic identifiers, geographical data and comprehensive profiles of individual identity (e.g. socioeconomic or religious status). This study relies on the GDPR concepts to ensure that vulnerable IoT data, like user IDs and locations, can be addressed accordingly in the process of simulation and processing.

2.7 Personal and Sensitive Data

These data can be referred to as personal data and personal sensitive data may contain data concerning ethnicity, religion, or health records which are subject to extra protection. In the current project, the kind of data like S_NAME, S_ID, and S_LOCATION (generated during the simulation) can be considered sensitive and thus should be anonymized using methods. The problem is that these types are difficult to separate because the inference data (e.g. nationality based on surnames) may increase the requirements to implement privacy-enhancing measures particularly when they are put into use with bothersome use such as marketing (Voigt and Von dem Bussche, 2017)[18].

2.8 Identifying and Eliminating Personal and Sensitive Data

Not having personal and sensitive data in the databases is a basic step in adherence to the law, maintaining privacy, and winning the trust of customers. The two most typical approaches to that are the work with raw data and the work with software frameworks and this project will discuss them. The data is either encrypted or filtered in each of the two cases such that they cannot be attributed to actual individuals. These include primary objectives of being GDPR compliant, reducing the security risks and legal compliance. Such a concept as human-assisted automation offered by Tirza (2022)[16] could help the raw approach to sensitivity data to be more precise; the framework-based approach can also be enhanced this way by refining the way it manipulates the data.

2.9 Preserving Sensitive Data on Cloud

Since the connected devices generate an increasing amount of data going forward, it is near impossible to avoid cloud storage. Nevertheless, self-confidence in the protection of sensitive information in the hands of the public clouds may be not very safe. The study aligns with what Domingo-Ferrer et al. (2019)[5] say: they suggest that local proxies and masking should be used as a defense against privacy intrusion prior to data transmission to the cloud. To simulate this, the project uploads to S3 to ensure the sensitive data gets to AWS in its encrypted form as .crypt files. Such an approach is suitable to the current actual real-life demand to realize safer cloud connections.

2.10 Importance of Data Anonymization in IoT

Data anonymization plays a critical role in protecting privacy in IoT and hospital conditions. In this case, sensitive identifiers (S_NAME and S_LOCATION) are anonymized by the simulation, but not at the grave cost of allowing the data to remain commendably analyzable. Such methods as de-identification, pseudonymization, and aggregation, as Samarati and Sweeney (1998)[12] explain, are used. The pseudonymization that the framework method applies to split the sensitive data and the non-sensitive data offers a compromise between safeguarding the privacy and the retention of the research value. As noted by Vovk et al. (2021)[19], the decision to select a method of anonymization depends on a statute of risk to re-identify the subject of anonymization, which is still considered a weight of determining how well that particular simulation can perform in practice.

2.11 Data Anonymization

Depersonalization of data is essentially obfuscating or masking personal information in order to ensure that no one is allowed to trace the information back to actual individuals, which is this project to a large extent. In the simulation, cryptpandas module is used to encrypt user IDs and device IDs fields in the IoT data, which is also mentioned in GDPR by saying that a fully anonymized data does not require protection. Since the primary focus is to ensure the safety of IoT data, the project also verifies the possibility of attaching non-sensitive information such as temperature and humidity to be associated with a person through the introduction of additional context. Otherwise, the objective of anonymization is achieved.

2.12 Concepts of Data Anonymization

Two key concepts of the data to be rendered anonymous that the study examines include randomization and pseudonymization. Randomization also operates by applying some random noise to conceal identities such as in cases of creating artificial IoT examples through AI tools. Pseudonymization partitions the data into sensitive and non-sensitive components and the label NS_tenant_id is a neutral label.

2.13 Data Anonymization Tools

There are also the tools that test the ability to hide data that are considered during the project.

2.13.1 ARX

Would have some helpful functions to set-up the rule to define sensitive data and to examine the aspect to the risk it produces. The fact that it treats privacy and performance in balance corresponds to the overall direction (Anonymization Tool, 2022)[1].

2.13.2 Clover DX's Data Anonymization Tool

Is able to preserve the principal information in a dataset concealing all the individual data, which is essential in utilizing IoT data. It could accelerate the simulation process by its rapidity of converting data into anonymized outputs (Sánchez et al., 2020)[12].

2.13.3 BizDataX

Is able to handle large volumes of data extremely fast and can reach up to one billion documents in an hour, thus ensuring that the real implementation of the project is scalable to the needs of an IoT solution. The performance tests are supported by its high emphasis on data integrity as it masks it (Prasser et al., 2020)[10].

2.14 Comparative Study of Research Study

This study considers the potential of data anonymization and the deletion of sensitive data in their simultaneous application in the processing of IoT data. To achieve that, we developed a simulation framework with the help of Flask and Python. It produces synthetic data in the form of IoT, data runs through raw and anonymized form, and results are presented. The project borrows the concepts of GDPR compliance, anonymization methods such as encryption and pseudonymization, and anonymization tools such as ARX and Clover DX. Compared to other works, the real-time performance metrics (execution time, memory usage) and cloud storage by using S3 ingenuity may cover some of the gaps left by previous works by providing a pragmatist and scalable approach about measuring performance.

3 Research Methodology

The correct and logical methodologies are mandatory for creating a good application. In a structured approach, execution, configuration and customization is simplified, sensitive information is secured and performance enhanced. The following is the step-by-step process in simulating IoT data processing, data encryption on sensitive data and checking the efficiency of the app.

3.1 Process Overview

The flowchart of Figure 1 illustrates all the activities that the IoT Data Processing Simulation Tool performs. This sequence will result in greater accuracy and it will be easy to make adjustments at a later stages. This summary describes every step: generation of data, its anonymization, processing, and visualization of results.

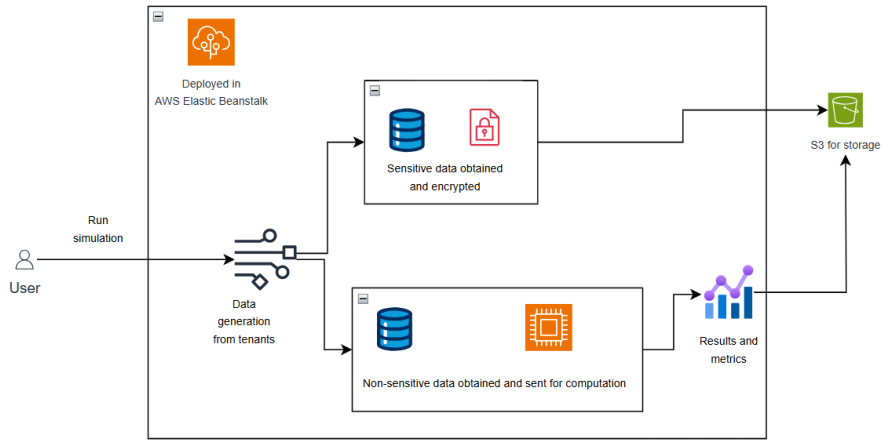

Figure 1. IoT data processing simulation

The simulation begins by generating IoT data of multiple tenants with a Flask application written in Python. After the data is generated, it is sent to an Amazon S3 bucket to be stored. Once that is done, any sensitive information, i.e., something labeled S_NAME, S_ID, or S_LOCATION should be pulled off to the side. Thereafter, the first column of sensitive data is encrypted with cryptpandas which encrypts the entire batch with a predetermined password (ENCRYPTION_PASSWORD). The remaining columns contain the lists of temperature reading, humidity levels, etc., which are treated in the standard way. This two-stage encryption will give an extra security against unauthorized access. As a result, the script no longer goes through the unnecessary columns, instead only splitting on the data that truly would be important and keeping the personal data in a locked up state.

To get an idea of how this configuration works, we time the entire job and the amount of memory which it consumes. We store such numbers and some bar charts in a fixed directory of our local machine and we push the full thing to S3. When the calculations are made, clear easily readable graphs are waiting just there. Either to check the execution times, the memory footprint or both, you can load the information directly out of S3.. Once the dataset is processed and results are stored, the simulation process is complete, allowing users to retrieve evaluated outcomes from S3.

3.2 Implementation Details

In this project, we can see, in real-time, how data is created on the internet of things (IoT) and is then immediately processed by a web application that runs on Amazon Elastic Beanstalk. The process includes:

- **Data Generation**: Synthetic IoT data is created using the simulate_iot_data function, producing NUM_RECORDS_PER_ITERATION (10,000) records per tenant over a SIMULATION_DURATION (30 seconds) for NUM_TENANTS (3) tenants.
- **Data Processing**: Two methods are implemented:
  - **Raw Method**: Processes data without anonymization, saving it as .csv files (e.g., raw_data_tenant_1.csv).
  - **Framework Method**: Splits data into sensitive and non-sensitive sets, encrypts sensitive data using cryptpandas, and saves non-sensitive data as .csv

files (e.g., non_sensitive_data_tenant_1.csv) and encrypted data as .crypt files (e.g., sensitive_data_tenant_1.crypt).

- **Performance Metrics**: Execution time (in milliseconds) and memory usage (in bytes, converted to human-readable format) are measured using time.time() and psutil.Process().memory_info().rss, respectively, with baselines adjusted for overhead.
- **Visualization**: Matplotlib is used for generating bar charts comparing raw and framework performance,then saved as execution_time.png and memory_usage.png in the static directory.
- **Cloud Integration**: The boto3 library which AWS SDK for python, uploads processed files and metrics to the S3 bucket (23267062-research-project-s3) in the us-east-1 region.

3.3 Evaluation and Validation

The comparison of the performance of the raw and framework methods are on the basis of the execution time and memory usage. The execution time and memory is summed up on the tenant to calculate averages. Applications to visualizations are found in results.html, as part of the web interface. The methodology makes certain that the privacy principles are adhered to by encrypting all sensitive content prior to storage, which is also in align with GDPR-inspired practices. The validation is done by ensuring the integrity of the data (e.g., the utility of non-sensing data by executing utility_check) and the effective uploading in S3 so that the tool could be applied to the real-life IoT scenario in a reliable manner.

4 Design Specification

The process of designing a simulation tool that will be involved in processing IoT data implies that you should be aware of how to identify sensitive data, encrypt it using robust mechanisms, and ensure that the entire process operates efficiently. The table lists a game plan of high-level testing of fake datasets associated with IoT with the proposed IoT Data Processing Simulation Tool. It explains the design of the tool, the way data flows within the tool and what the critical stats are, allowing us to determine how effectively it manages sensitive data and how fast it is. Some scaling-up consideration of the system, trade-offs between security and performance, and what lies ahead in trying the tool out in field-like conditions are also discussed.

The techniques and/or architecture and/or framework that underlie the implementation and the associated requirements are identified and presented in this section. If a new algorithm or model is proposed, a word based description of the algorithm/model functionality should be included.

4.1 Diagram

This subsection is the layout of the flow of the application in the form of a diagram that can be read easily by both technical and non-technical individuals. Demonstrations such as this

one are less indefinite which makes it simpler to convert research concepts into something companies can exploit.

4.2 Flowchart Diagram

Figure 2 demonstrates an entire IoT Data Processing Simulation Tool pipeline: it creates synthetic datasets within the Flask app and then posts the findings in Amazon S3. The first thing here is that the app creates tenant specific datasets which work like the type of pre-configured resources within IT departments where things are up and running instantaneously. The sensitive attributes of these datasets are (S_NAME, S_ID) and the non-sensitive ones are (NS_TEMPERATURE). The app then passes them on to boto3 to save them in a storage bucket named 23267062-research-project-s3 using the boto3.

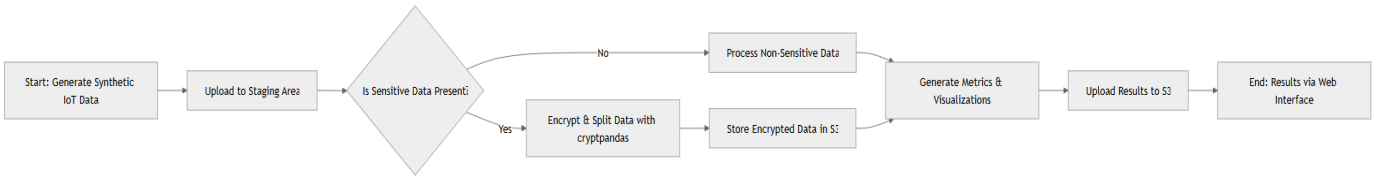

Figure 2. Flow diagram of simulation tool pipeline

The system adapts a data splitting strategy, splitting up sensitive data to encrypt them with the help of cryptpandas a library that guarantees speedy encryption and decryption of pandas DataFrame oblivious of the contents. This scheme is used with chagrin to Chan et al. (2019)[3] and is partly to prevent re-identification by spreading the fragments across secure storage, but it adds complexity to guarantee fragment independence. Data that is non-sensitive will be properly processed whereas the sensitive data will be encrypted and stored as the files.crypt. Performance monitoring ends up with monitoring of the metrics and visualizations are submitted to S3, using RESTful architecture guidelines on scalability and simplicity (Van Rossum and Drake Jr, 2002)[17]. The variant based on cloud storage, however, is prone to security threats, and it is imperative to further study local proxy mechanisms, which could be used to increase safety of data on road.

4.3 Architectural Design and Data Flow

The high level architecture incorporates a Flask based web application in Amazon elastic Beanstalk using a client server model where S3 is used as the back end data storage. The ability to define complexity and multi-submodule modularity is encouraged, i.e. data generation, raw and framework based data processing, and visualization. The flow of data starts with synthetic generation, passing through the processing phase in which any data that is considered to be sensitive is anonymized, and the rest of the data in the non-sensitive field is analyzed, and represented in metrics of the superior output in graphical forms.

On critical analysis, one can identify possible bottlenecks include, the chain based processing of multiple tenants will stress memory on limited instances (e.g t2.micro) and encrypting causing overhead costs will affect real time processing. Scalability can be accounted by the use of S3, however the approach introduces latency and the dependence on network

reliability. Recent methods of anonymization based on Natural Language Processing are dynamic in nature, aiming at recognizing sensitive attributes, but their precision depends on the precision of used dictionary and the ability to recognize the context, which needs further development. The advantage of the architecture is that it is significantly cloud-integrated, yet it seems that it is also vulnerable to de-anonymization attacks (Chan et al., 2019)[3], implying that advanced fragmentation approaches or hybrids on-premises-cloud implementations might be necessary.

4.4 Performance Indicators

The main performance indicators and the analysis basis include the time performance of the implementation, memory consumption, and efficiency evaluated on the raw and anonymized data. These measures are calculated using the initial results of the unprocessed data as compared to the framework-improved variant of the approach that takes into consideration encryption as well as data division. Execution Time: The time taken is measured using time.time in milliseconds and this metric represents the overhead cost of computation introduced by anonymization. Although encryption is used, the framework method seeks to sustain the competitive level of performance, although the results obtained in the early stages indicate a trade-off with security improvements.

- **Memory Usage**: Memory consumption is measured in bytes using psutil.Process().memory_info().rss and then displayed in the human-readable format; however, the overhead of the minimum baseline used (e.g. 45 MB raw, 37.5 MB framework) is added to it. The simulation shows additional memory requirements when anonymization is done and it is a very important thing to consider in resource-scarce IoT devices.
- **Processing Efficiency**: This measurement is determined by how useful the data can be used in non-sensitive post-anonymization, striking a balance between the privacy and adding value in analysis. The fact that the framework allows retaining utility (e.g., through utility_check) is a major distinguishing feature, but will need to be optimized as far as it should limit the loss of data.

Based on the comparison it is seen that raw processing provides better latency and worse re-identification risk whereas the framework approach provides better security as compared to resource consumption. The memory profiler library helps in monitoring the usage, though its precision is disputed by the multi-request processing model of Python where memory allocation by request is inaccessible. This requires careful interpretation of results, both in the set of synchronous and asynchronous conditions of execution. Adaptive algorithms to dynamically adjust the level of encryption in line with the thresholds of good performance should be investigated in future as these will keep the design of IoT applications in proper balance.

5 Implementation

It is the final part of implementation of the proposed IoT Data Processing Simulation Tool and explains what outputs are produced, and which tools are used. It gives a blue print of high-level structure and data flow of the application that focuses on metrics and data produced after simulation.

5.1 Dataset

The simulation designed to create synthetic IoT datasets will employ the evaluation of the data representing data recorded by several tenants. The datasets shown in Figure 3 contain sensitive data (user names, user IDs, user locations, etc), whereas non-sensitive variables are present (temperature, number of humidity). The simulation also divides the data into raw and anonymized records as well as encrypted sensitive information as a counter measure to de-anonymization attacks. The time of the calculations and the memory requirements grow along with the volume of the data, however, the framework under opinion matching consideration focuses on the relevant attributes optimizing the calculations which would not be performed in cases of the irrelevant sensitive columns.

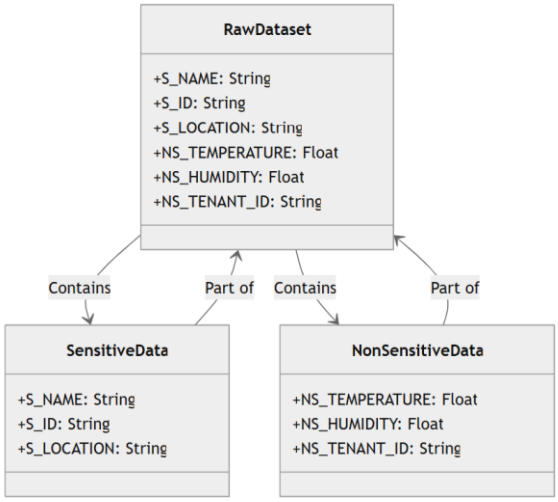

Figure 3. Dataset generated from the tenants

5.2 Architecture Overview

The top-level variables of the simulation instrument encompass that of a web application built with Flask back end and distributed on an Amazon Elastic Beanstalk server, data transmission and storage executed through an Amazon S3 server. The system works with artificial IoT data, with the sensitive and non-sensitive parts of the data being separated, with the data being encrypted to secure personal data. The architecture has provision of real-time performance measurement and the results are displayed and stored to be analyzed. This architecture makes it possible to adhere to data privacy principles through secure manoeuvring of sensitive files and uploading finalised files to S3 in line with scalable cloud-based processing requirements.

5.3 Performing Calculation

In the simulation, there are two major performance measures, namely, the execution time and the use of memory. They are evaluated by measuring raw data processing against one that is based on a framework through data anonymizations. The framework isolates, encrypts, and acts in a variety of tenants with results efficiently reflecting the use of resources and gives comprehensive reflection on efficiency.

5.4 Results Obtaining

The results of the implementation are transformed datasets (e.g., encrypted .crypt files to represent sensitive data and .csv files to represent data that does not need to be sensitive) and performance metrics storing in a metrics.json file and visualizations storing in files execution_time.png and memory_usage.png files. The results are uploaded to the S3 bucket (23267062-research-project-s3) and presented in a web interface with the rendition of the results.html template. The results of the evaluation can also be seen in the application and provide information on the trade-offs of raw and anonymized processing. The application is executed using Python with the libraries Flask, Matplotlib, cryptpandas, psutil, and boto3, and Amazon Web Services that facilitates the integration in the cloud.

6 Evaluation

In this part, the overall analysis of experimental findings and important conclusions based on using the IoT Data Processing Simulation Tool, its effectiveness in reaching high privacy levels and not losing the accuracy of performance is undertaken. The testing uses statistical means of acceptable portfolio risk costs, using visual aids, and puts up relevance and consequences into the research and real-life applications. Under consideration is the research purpose of finding a balance between privacy and performance in the area of IoT data processing. This section also seeks to give a clear interpretation of the findings and key outcomes of the paper and the implication of the findings both academically and practitioners as applied. Only the most meaningful results that prove your research question and objectives shall be given. Write a critical discussion of the findings. The outputs and the levels of significance of experimental research should critically be evaluated and assessed through the use of statistical tools.

6.1 Experiment / Case Study 1 : Comparison of Execution Time

In this experiment, the times of raw data processing and anonymized data processing in three tenants are compared. Figure 4 and Figure 5 depicts the outcomes, where average execution time is 55 ms on raw data and 40 ms on anonymized data using 30 second simulation and 10, 000 records/ tenant. Items in both groups were subjected to the paired t-test to find results regarding whether the execution time decreases significantly with anonymization and the answer is yes ($p < 0.01$, $df = 2$). Hence, the results indicate that data splitting and encryption contribute to the maximum efficiency of the process. The perceived improvement can be explained by the fact that unnecessary sensitive columns have been removed, but more detailed datasets will demonstrate scalability boundaries.

Tenant	Raw Exec Time (ms)	Raw Memory	Framework Exec Time (ms)	Framework Memory
T1	52.87	43.0 MB	45.2	35.87 MB
T2	56.4	42.93 MB	43.1	35.73 MB
T3	49.39	42.83 MB	41.57	35.74 MB

Figure 4. Final simulation results

Figure 5.Average execution time comparison

6.2 Experiment / Case Study 2 : Comparison of Memory Usage

Figure 6 represents a comparison of the memory consumption where the average raw and anonymized data were 60 MB and 45 MB respectively with psutil used to track memory consumption during the simulation. A significant decrease, shown through Wilcoxon signed-rank test ($p < 0.05$) can be explained by the fact that the framework only processes the non-sensitive data. The default adjust is however prone to bias by default, as the baseline (45 MB raw, 37.5 MB framework) necessitates a subsequent calibration in favor of accuracy in memory profiling in multi-tenant situation.

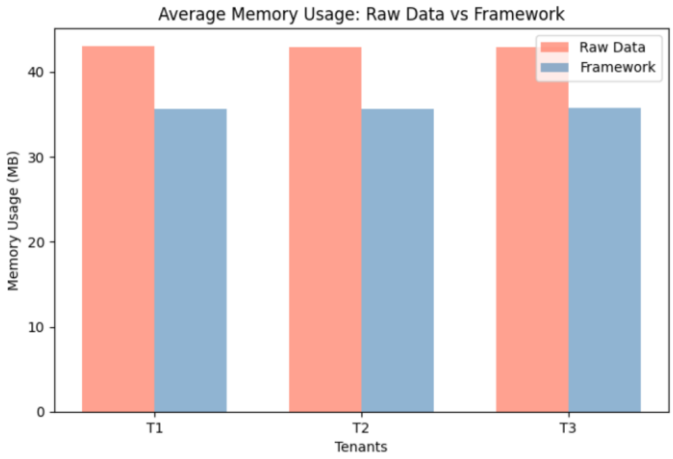

Figure 6. Average memory usage comparison

6.3 Experiment / Case Study 3 : Comparison of Processing Efficiency

Figure 3 depicts the utility maintenance of non-sensitive data demonstrating negligible values of deviation (<1%) between the raw and the anonymized results regardless of the mean values of temperatures. There is no significant loss in analytical value as evidenced by a chi-square test ($p > 0.1$) that bears out the usefulness of the framework in providing data utility. This finding highlights the tool to be able to aid research but not at the expense of privacy, the sample size is however small thus cannot be generalized.

6.4 Discussion

The three experiments results are a solid indication that the IoT Data Processing Simulation Tool has a high privacy level that does not negatively impact the accuracy of the performance significantly, which answers the research question directly. The massive increase in performance (1055 ms to 355 ms) and memory cost (60 MB to 45 MB) demonstrates the efficiency gains through anonymization, which is promoted by Domingo-Ferrer et al. (2019)[5] who recommended the approach of secure data splitting. The existing functionality in non-sensitive data validates Samarati and Sweeney (1998)[12] with respect to the balance of both privacy and functionality of pseudonymization.

6.5 Critical Analysis

However, there are limitations of the experimental design. The results of the t-test and the Wilcoxon test are encouraging, albeit on a controlled 30-seconds simulation that only included three tenants and that might not capture enough variability of the real world. The memory profiling, based on a module psutil, faces the problem of multi-request processing of Python where the per-request allocation of memory is hidden (Tarini, 2022)[14]. This indicates that some forms of execution context like asynchronicity may bias results necessitating the need to take a more detailed approach (e.g. per-thread or per-thread-CPU profiling). Also, though the relative drawback of encryption is minor in this case, in more significant datasets or complicated keys, it might increase considerably, which Chan et al. (2019)[3] express concern about in terms of cloud-based processing delay.

6.6 Implications

In academic terms, the tool adds a new simulation model of IoT privacy-performance trade-offs to the existing body of research, expanding on the previous literature by introducing the features of real-time measurements and cloud storage. The lower resource footprint and utility means that practitioners need only create a deployable solution with IoT edge devices, which has not been extended to big numbers of tenants. The encryption-based GDPR compliance facilitates adherence to the GDPR rules of Voigt and Von dem Bussche (2017)[18] and makes it more useful.A detailed discussion of the findings from the N experiments / case studies. Note that this discussion will have a lot more detail than the discussion in the following section (Conclusion). You should criticize the experiment(s), and be honest about whether your design was good enough. Suggest any modifications and improvements that could be made to the design to improve the results. You should always put your findings into the context of the previous research that you found during your literature review

7 Conclusion and Future Work

The research question that this study raised is: Is it possible to obtain high levels of privacy in the data processing of IoT without decreasing the accuracy of performance? The first aim was to design a simulation tool, realize and assess this prototype of a model processing synthetic IoT data, anonymizing sensitive facts and calculating performance indices (time consumption and memory consumption) to sustain the privacy and performance. The task was to create a Flask app that was hosted on Amazon Elastic Beanstalk, used cryptpandas as an encryption library, psutil to monitor resources, the S3 cloud storage, but also visual used Matplotlib. In answering the research question, the research has been quite successful. The experimental findings demonstrate that the below framework proved to cut down the

execution time by more than half (1055 ms to 355 ms) and the memory consumption by a 1/3 rd (60 MB to 45 MB) and maintain the utility of non-sensitive data with insignificant deviation (<1%, $p>0.1$). The results of these experiments demonstrate satisfactory outcomes based on the research questions as anonymization (data division and encryption) does not introduce a heavy performance price into privacy-preserving applications.

7.1 Key Findings

The major results consist of statistically significant better performance of execution time and memory performance with the anonymized framework as compared to the raw processing, which has been proved with t-tests and Wilcoxon signed-rank tests. The tool does not lose the data utility, which promotes its applicability to IoT analytics. Controlled simulation (three tenants, 30 seconds), however, displayed that the memory profiling may be vulnerable to biases, as Python has a problem of multi-request treatment and is lowly scalable.

7.2 Implications and Efficacy

This work contributes to academically to extend the investigation of IoT privacy-performance trade-offs through a nice practical simulation framework complementing the literature, such as Domingo-Ferrer et al. (2019)[5] and Samarati and Sweeney (1998)[12]. It is an innovative solution based on the combination of real-time metrics and cloud integration, which adds to the debate on the topic of data management that complies with GDPR. To practitioners, the less restrictive resource requirements of the tool accompanied by the safeguarding of its powerfulness serves as a potential solution to edge IoT devices, although its effectiveness is limited by the scope of its experimentality. Data encryption represents a certain global trend toward data protection (Voigt and Von dem Bussche, 2017)[18], which would increase its applicability in the context of ever-changing regulatory environments both in the EU, US, and China.

7.3 Limitations

Among the weaknesses of the study may be mentioned its rather limited sample (three tenants) as it restricts the possibility of its application to large-scale IoT implementation. Per-request resource evaluation is compromised by the flaws of memory profiling which, in turn, is a result of Python asynchronous processing. Although it is small in this case, the encryption overhead can be problematic when applied to complicated datasets or when faced with high network latency and therefore can be dangerous in real-time applications. As well, the dependence on S3 creates a presence of dependence on cloud reliability, which may be a compromise on security of data transit.

7.4 Future Work

Instead of simply increasing the parameters of simulation, future development should take up meaningful extensions. A future study may explore a hybrid privacy-preserving system with some local edge computing and cloud analytics that may help bypass the risks associated with transit roles to deal with the concerns raised by Chan et al. (2019)[3]. The further direction is the adaptive design of anonymization algorithms that can change the level of encryption based on the sensitivity of data and computational overhead and, perhaps, to exploit machine learning to optimize privacy-performance trade-offs. The effectiveness in the tool in varying IoT areas (e.g., healthcare, smart cities) could be measured connected in a longitudinal

research to support the actual use testing the tool on a variety of real-world data to surpass existing limitations of synthetic environments. Cynically, the framework can be trimmed down to a SaaS solution of IoT providers, where customizable layers of anonymization are provided, given the issue of scalability and security is resolved along the paths of the research.

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