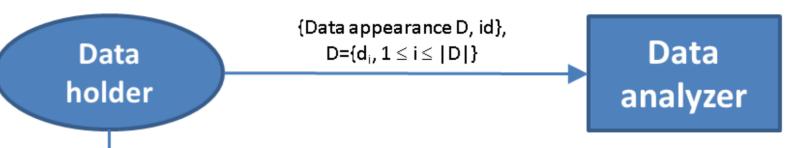


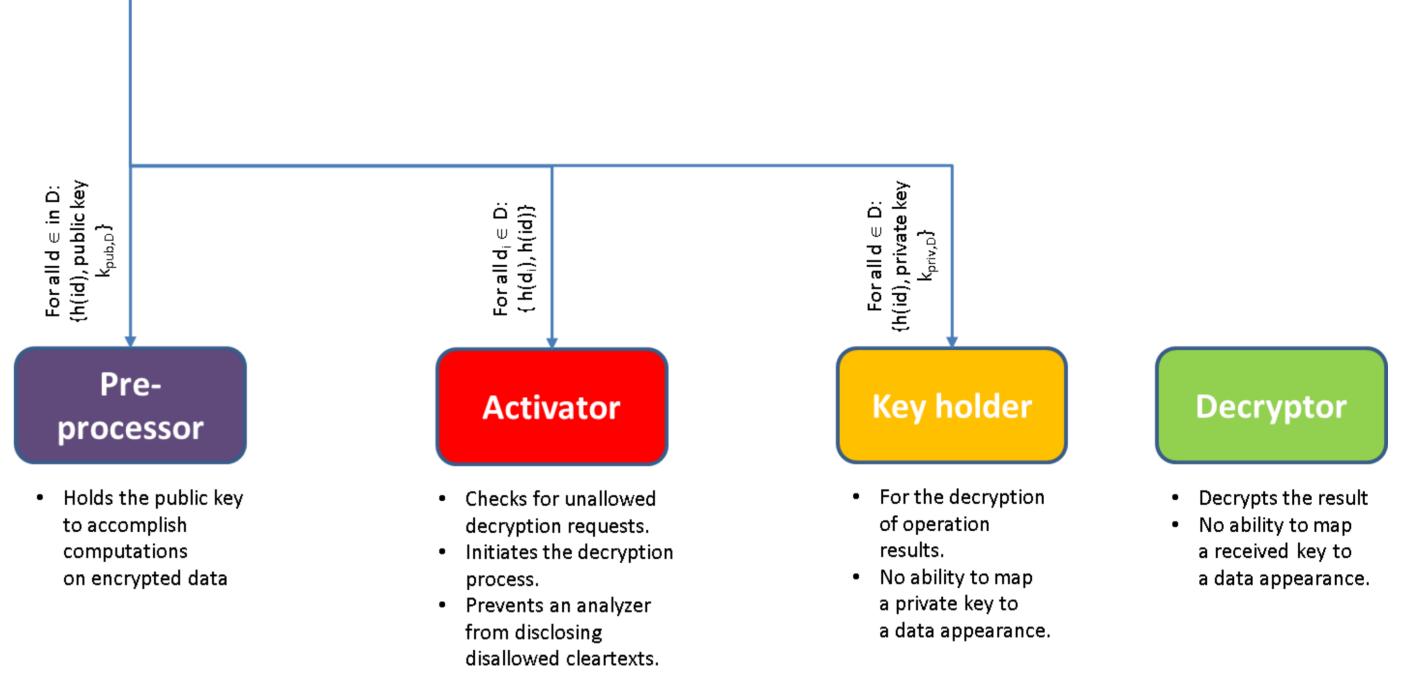
# A Framework Design for Privacy-Preserving Computation on Shared Data

#### **1.** MOTIVATION

When information is shared among multiple parties for data analysis, the objective of the data holders in keeping cleartexts confidential for privacy collide with the objective of the data receiver in the highest achievable utility. Consider the following application scenario: Data holders want to share log files (e.g., see [1]) with a centralized analysis entity, called data analyzer. The data holders are interested in the results of the analysis performed by the analysis entity. The analysis entity profits from collecting log files from multiple sources because it gives him a broader view on the field, e.g. on the current situation regarding certain attacks in a business area. On the other hand, the data holders want to keep their data confidential. One reason is the privacy concerns of the data owners. This contradicts the data analyzer's interest in data utility. The described contradiction may prevent different parties from information sharing and hence, decreases the chances to profit from the analysis of data collected from multiple parties. We propose a solution that meets both the privacy and utility needs of the information sharing parties. We assume that he data holders and the data analyzer agrees on the utility required for data analysis in mutual agreements called policies. A policy is a set of conditions to be fulfilled by the exchanged data in order to meet all the utility options satisfying the analyzer's and the holders' requirements. This may include the ability to calculate overall sum of numerical data for statistical analysis, or to disclose IP addresses in a log file under certain conditions, or to check encrypted data for equality. The conditions stated in a policy must be selected very carefully to ensure that the privacy of the data owners will be preserved. For formulating such policies, we refer to [2]. Before sharing the data with the analyzer, the data holder must transform the data to a data appearance that meets the formulated policy. Depending on the use case and the sensitivity of the data under consideration, the selection of the provided utility must keep most of the information confidential so that an attacker would not be able to use the utility properties of the data appearances for attacks utilizing information linkage or correlation with external information. In order to solve the problem described above, one approach is the utilization of homomorphic encryption. In homomorphic encryption, the cleartext data p1; p2 are encrypted with an encryption mechanism E to E(p1); E(p2), respectively. E ensures that certain operations can be performed on E(p1) and E(p2) and are equivalent to operating on the plaintexts p1 and p2. That means, E(p1)\*E(p2) = E(p1+p2) for appropriate operations \* and +. Note that the result of the encrypted computation is encrypted. In the above-mentioned application scenario, the data holder would use an appropriate homomorphic encryption mechanism to encrypt the cleartext content of the log files to data appearances. Depending on the selected homomorphic encryption mechanism, this would allow the analyzer to perform certain operations on the received encrypted data. To disclose the result of an operation to the analyzer, it must be decrypted. This usually requires knowledge of the secret (private) key and comes together with the fact that having access to the private key enables the data analyzer to decrypt the content of the data appearance and hence, violating the privacy of the data owners.

## **3. PROTOCOL INITIALIZATION AND DATA DISTRIBUTION**





#### **Security Assumptions:**

- Honest-but curious adversarial model.
- The pre-processor has no access to private keys.
- The key holder and the decryptor cannot map an arbitrary d ∈ D to the correct private key.

### PERFORMING OPERATIONS AND RESULT DECRYPTION

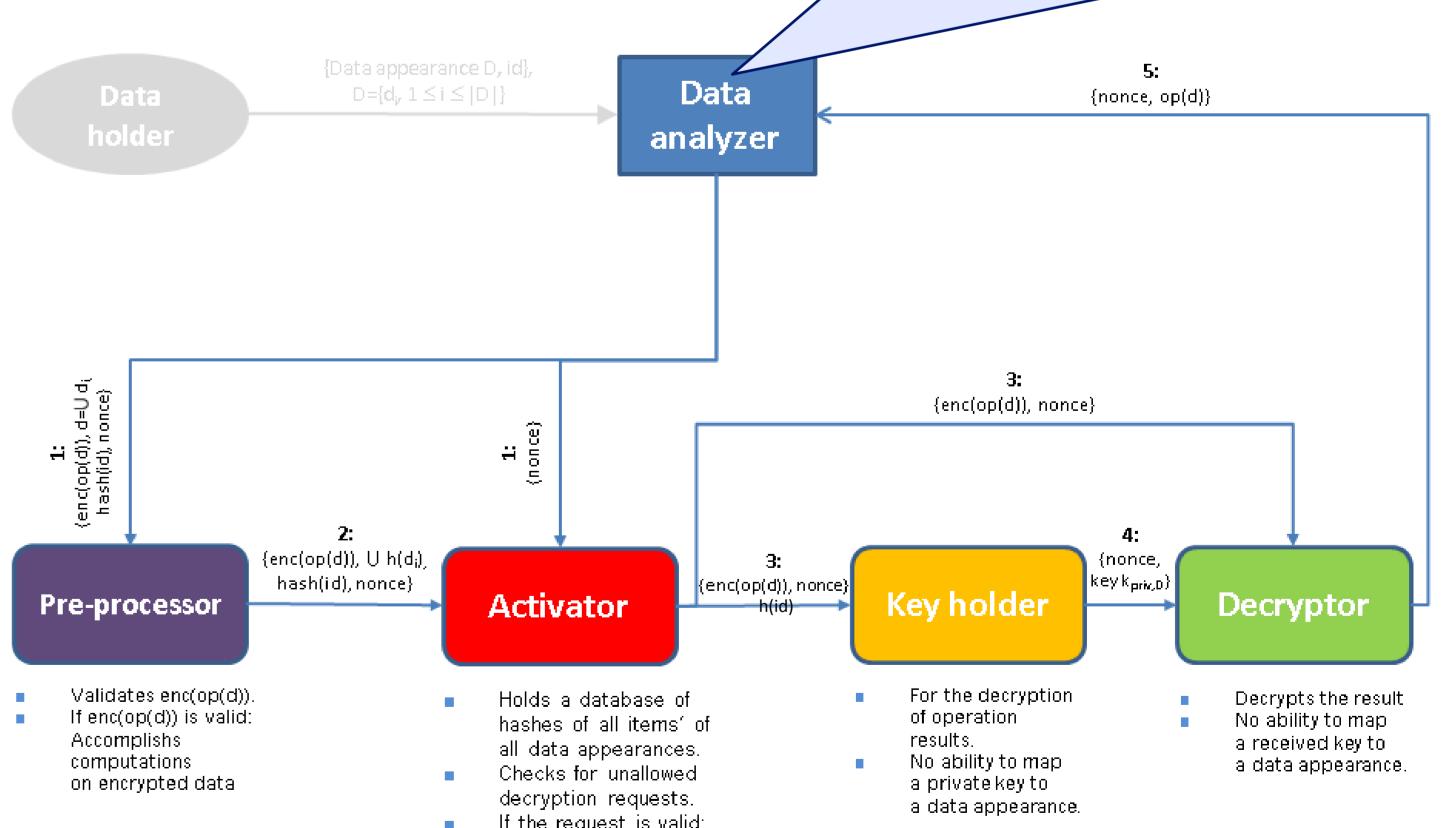


Data		Data
holder	Availability policy	analyzer
Inciden		anaryzer
<ul> <li>Holds all the cleartext data from (multiple) data owners.</li> <li>Wants to share parts of the information contained in the data with the data analyzer.</li> </ul>	The data holder wants to share information with the analyzer. Both will profit from the analysis of data from multiple sources.	<ul> <li>Goal: retrieving</li> </ul>
	The data holder wants to preserve the privacy of the data owners by keeping the cleartexts confidential.	information from data analysis.
	To be able to perform the analysis operations, the data analyzer needs certain properties of the cleartexts made available, e.g. he may require to calculate overall sums of data items.	<ul> <li>May be curious about further cleartext content</li> </ul>
	The data holder and the data analyzer <b>agree</b> on the properties of the cleartext data that should be available for the data analyzer. They state the agreement in a machine-readable <b>policy</b> .	
Constraint: keeping the cleartext values confidential.	The data holder creates data appearances that fulfill the policy agreement, i.e. he creates a data representation of the cleartext data that contain no other information. Any information contained in the cleartexts, but not formulated in the policy, will not be available in the data representation.	
	<ul> <li>Depending on the agreed properties, the data appearance may contain homomorphically encrypted items to enable the data analyzer to perform operations on encrypted data without being able to decrypt the cleartexts</li> </ul>	
	Finally, the data holder transmits the data appearance to the data analyzer once. After the transmission, the data analyzer is able to perform the required operation without any further communication with the data holder.	

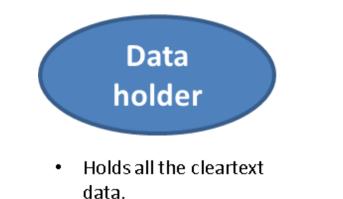
For the decryption of encrypted results of operations on encrypted data, the data analyzer uses the decryption process of the framework.

#### Given: Data appearance $D = \{d_i, 1 \le i \le |D|\}$ .

- $d_i$  is the a homomorphically generated ciphertext enc( $p_i$ )) of a plaintext  $p_i$ ,.
- Goal: compute  $p_k + p_l$  by computing  $d_k * d_l$  for appropriate + and \*.
- Problem: Confidentiality of p<sub>k</sub>, p<sub>1</sub>.
- Solution: The data analyzer is not allowed to decrypt, but he requests for a decrypted result.
- Constraint: The data analyzer should not ne able to cheat using homomorphic properties of the encryption mechanism (here: Paillier [3]).



# 2. STAKEHOLDERS



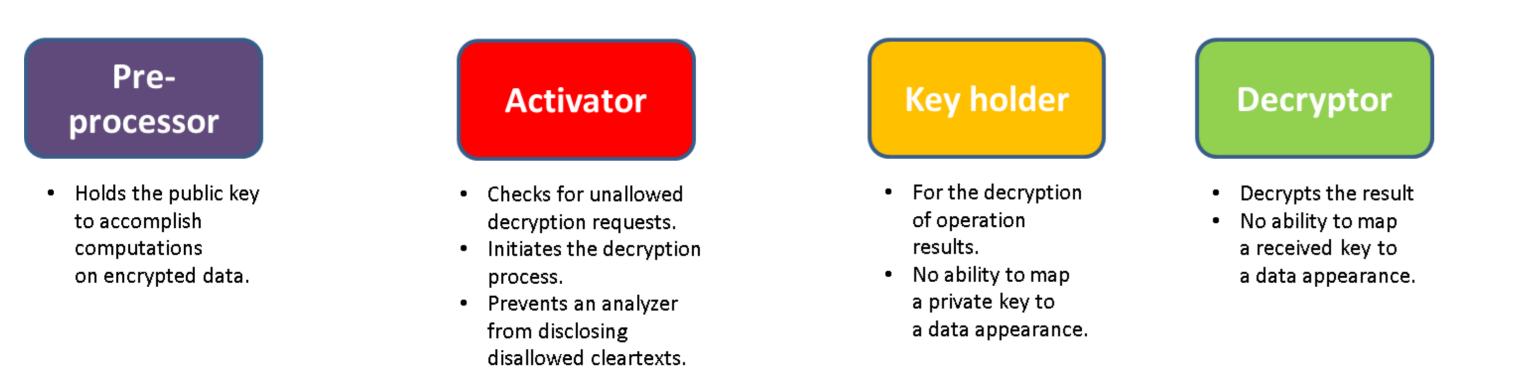


 Goal: retrieving information from

Wants to share parts of the information contained in the data with the data analyzer.
Constraint: keeping the cleartext values

confidential.

data analysis. • May be curious about further cleartext content.  If the request is valid: Initiates the decryption process.
 Prevents an analyzer from disclosing disallowed cleartexts.



#### **5.** SOURCES

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[2] S. Kasem-Madani and M. Meier, "Definition of Availability Policies for Data Pseudonymization Using XACML,"
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Available: <a href="http://www.ifip-summerschool.org/">http://www.ifip-summerschool.org/</a>
[3] P. Paillier, "Public-Key Cryptosystems Based on Composite Degree Residuosity Classes," in Advances in Cryptology, EUROCRYPT 99, ser. Lecture Notes in Computer Science, J. Stern, Ed. Springer Berlin Heidelberg, 1999, vol. 1592, pp. 223–238.

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