Secure Parallel Processing of Big Data Using Order-Preserving Encryption on Google BigQuery

Timo Schindler  
Faculty of Computer Science  
and Mathematics  
Laboratory for Information Security  
OTH Regensburg  
timo.schindler@oth-regensburg.de

Christoph Skornia  
Faculty of Computer Science  
and Mathematics  
Laboratory for Information Security  
OTH Regensburg  
christoph.skornia@oth-regensburg.de

Abstract—With the increase of centralization of resources in IT-infrastructure and the growing amount of cloud services, database management systems (DBMS) will be more and more outsourced to Infrastructure-as-a-Service (IaaS) providers. The outsourcing of entire databases, or the computation power for processing Big Data to an external provider also means that the provider has full access to the information contained in the database. In this article we propose a feasible solution with Order-Preserving Encryption (OPE) and further, state of the art, encryption methods to sort and process Big Data on external resources without exposing the unencrypted data to the IaaS provider. We also introduce a proof-of-concept client for Google BigQuery as example IaaS Provider.

I. INTRODUCTION TO ORDER PRESERVING ENCRYPTION

Cloud Computing has reached to be one of the cornerstones in IT-Infrastructure during the last years. Especially the outsourcing of databases is one main service and has been proposed in several publications. [11], [2], [3], [4], [5], [6], [7] The idea to use complex networking and computing infrastructure as a service is reasonable but has its limitations. [8], [9] An external platform of data storage has to be treated as untrusted. Encryption is a powerful technology for protecting the confidentiality of the data stored but needs to be decrypted for processing. One approach is to use encryption which allows operations on encrypted data. Fully Homomorphic Encryption (FHE) and Order-Preserving Symmetric Encryption (OPE) are relevant approaches to solve this dilemma with encryption algorithms. As OPE maintains the order of the encrypted data obtained, data can be compared on the encrypted system and are thus sorted. Since the comparison of data is already sufficient to run a significant amount of common operations on the remote database system, this method fulfills two important prerequisites for the outsourcing of DBMS: Data can not only be securely stored, but also processed on a remote system. Because of this quality, OPE is primarily used in databases for processing SQL queries over encrypted data [10], [11], [12], [9], [13], [14], [15], [16], [17], [18]. The concept of OPE is subject of research since a number of years and secure algorithms were found. [10], [17], [19] The challenge for researchers is to develop a feasible solution for relevant use cases of secure data processing. Some of the most recent aspects are considered and evaluated in this work.

In the context of the outsourcing process of computing power and services to external, untrusted systems, Fully Homomorphic Encryption is an alternative to OPE. In contrast to OPE, FHE offers the advantage that the homomorphic property of the encrypted data is retained. Thus, an OPE scheme only guarantees that comparison’s plaintext space \((x > y)\) has the same result as those obtained in the encrypted space \((\text{Enc}(x) > \text{Enc}(y))\). In FHE, computation of more sequential operations on encrypted data are possible. Recent work on FHE has shown it is, in principal, possible the perform arbitrary computations over encrypted data [20], the performance overheads are prohibitively high, on the order of \(10^9\) times [10], [21]. Both procedures have their specific use case and can be used together. In this work we focus on OPE as we are mainly interested in the option to sort data on the untrusted IaaS-Platform.

Different OPE algorithms with specific characteristics are known [11], [22], [23], [10]. Mutable Order-Preserving Encoding (mOPE), a special form of OPE, is introduces by Ada Popa et. al. in [10]. With mOPE, the data on the server is encoded in a binary search tree (see fig. 1). The server provides the encrypted data stored in a binary tree and the OPE encoding path. The plaintext shown behind the encrypted cipher text (see fig. 1) is not known to the server and is provided with the purpose of the readers’ information.

For our implementation we use AES, an existing deterministic encryption algorithm with a constant initialization vector. The encrypted data is represented in a binary tree, in such a way that the right child node is growing and the left one is decreasing. For all commercial IaaS NoSQL providers, it is not possible to implement own methods and algorithms for storing data. mOPE can be modified and used in a IaaS NoSQL scenario without losing security or ordering qualities. As proven in [10] the only information revealed of the encrypted data is the order and hence the needed minimum of additional exposure. Due to the high security and simplicity this algorithm has been chosen for the following application scenario. The objective of this work is to propose a way to use the secure OPE algorithm mOPE on a cloud platform. The adaption of the mOPE algorithm is not possible without changing the way, data will be encrypted and sent to the cloud database due to the fact that cloud databases works in a different manner. In this work we discuss different challenges and possible solutions processing Big Data in a fast way by many clients.
II. USING ORDER-PRESERVING ENCRYPTION ON BIG DATA

There are different reasons for storing big amounts of data on potential untrusted databases, such as autonomous cars, intelligent homes or smart grids. However, Big Data is not restricted to new, expensive applications of big corporations, but Big Data can be acquired, also from small companies [24]. Big Data, being generally unstructured and heterogeneous, is extremely complex to deal with via traditional approaches, and requires real-time or almost real-time analysis. [25] In our scenario, Big Data needs to be accessed from many applications or users and be processed in a fast way. This is a widely used scenario for any kind of data. To work with Big Data also includes the use of NoSQL Databases, because of the horizontal scaling. A NoSQL database system is a database without a relational data model. NoSQL is perfectly suited for processing Big Data, because of the horizontal scaling. Contrary to vertical scaling (e.g. SQL-Server), where a single note needs to be upgraded to get more computation power, horizontal scaling simply needs more nodes. [26] This model is cost efficient and can be combined with an IaaS model. Thus, extremely large data can be processed in a fast way. Due to the use of programming models like MapReduce [27], which is used in several NoSQL Databases, the processing of Big Data is feasible possible. With OPE on a scalable cost efficient NoSQL resource, no expensive infrastructure is needed and the external resource is capable of a secure analysis of Big Data.

The keys, used to encrypt and decrypt the data, will be kept secret. The sorted and encrypted data will then be sent to the external service. Once the data is uploaded, many clients can perform analyses on it. In general, there is nearly no limitation on the clients or the complexity of the queries, because of the horizontal scaling of NoSQL Databases. The clients themselves can have different privileges. In the example configuration in figure 2 the client can have access to the secret keys. This is not necessary to perform queries on the data. If they do have the secret keys of the encryption proxy, the full range of analysis is possible. It may be possible that encrypted and unencrypted data are present in a single dataset. A client who does not possess the secret keys, can still perform analysis on unencrypted data. This scenario is conceivable, if some of the data in a dataset is public or available unencrypted. The unencrypted data can then complement the encrypted data by providing additional information and might be useful to perform other analyses. This concept allows several other security models and it is also possible to extend the concept for using different keys for different clients. With this concept, we have created a way to use the powerful computation power of the cloud-service Google BigQuery by many clients but not revealing information about the data, which will be stored in the database. Furthermore, due to the use of different keys, a highly granular rights management for the clients is also possible which can access different information without using or implementing any rights-management on the IaaS provider side.

III. THE INFRASTRUCTURE OF MUTABLE ORDER-PRESERVING ENCRYPTION ON GOOGLE BIGQUERY

To order and encrypt data the plaintext has to be known to the system encrypting it. Because this work can not be outsourced to an untrusted service, we use a central proxy configuration. Figure 2 depicts our concept for order-preserving encryption in an IaaS infrastructure. The concept of encryption includes an encryption proxy, an NoSQL-like IaaS and $n$ clients. The encryption proxy gets a Big Data chunk as input. The proxy orders and encrypts the data by using private keys. In this concept, it is also possible to use different encryption algorithms and keys for different columns of the data. The encryption proxy in between the Big Data and the IaaS provider is necessary, so no additional information besides the order will be revealed to any external resources.

A. Limitations on Order-Preserving Encryption for Big Data

Big Data usually implies that the amount of data cannot be processed by a single machine as the proxy in the described concept (see fig. 2). Also, the Big Data chunk will usually grow over time. This limitation does not only apply in this scenario, but is present every time, the order of encrypted data is needed. If new data will be added, the already encrypted and sorted data needs to be read from the external resource, decrypted, and sorted again. Outsourcing this operation to the external IaaS Provider does also reveal the private key to this provider. For security reasons, this approach is not possible. The concept we use offers the possibility to access data very fast because of the high power of the IaaS provider but still needs high computational power or time for encrypting the data on the encryption proxy.
B. Solving the Limitations

To solve the limitation on ordering and encrypting Big Data, we propose different approaches:

- **Using a high sorting range**: A resorting and reencryption is just needed if the plain text space size (domain) reaches a collision in the mapped sorting items (range). Then a new item cannot be sorted to the right position because of creating a collision. This can be prevented by choosing a much higher range space. A resorting and reencryption is more unlikely.

- **Partial encryption**: In many cases, Big Data consists of a mixture of public and private data. Only when private data and public data are brought into relationship, the public data is interesting for a potential attacker. A distinction has to be drawn between data that should be kept secret and data, which is public available. This can lead to a major decrease of the encrypted data by simply using an intelligent encryption schema on the Big Data.

- **Use of diverse encryption algorithms**: One data chunk consists of various kinds of data, with different claims on encryption. In order to know the right algorithm, the plaintext data needs to be analysed. If, for example, sorting is irrelevant because a data chunk contains the name of patients, this data can be encrypted with a probabilistic algorithm. This procedure can be parallelised and will affect the resources of the encryption proxy less.

- **Separating data chunks on server and merging it on client side**: We proposed an import of the Big Data as chunks. Assuming the returned queries results are significant smaller than the particular data chunk, the uploaded data chunks can be uploaded in different tables. A query then will be applied to the different chunks and the client will merge the much smaller results locally. By using this approach it is not necessary to reencrypt already uploaded chunks. If the fragmentation grows over time, a garbage collection can merge data chunks, reencrypt those and upload it again to the service to lower the tables on server side.

Additional approaches for solving the limitation can be the use of local NoSQL structures for the encryption and sorting proxy or the decreasing of the amount of data by just using the needed columns for OPE. [28]

IV. GOOGLE BIGQUERY AS EXAMPLE IaaS PROVIDER

Google BigQuery is a system, designed to perform SQL-like statements over Big Data. Google BigQuery can query 1 TB [24] and returns the result of the particular SQL statement. To achieve this, BigQuery uses different techniques of storing and processing data. They are based on several main systems, like BigTable, a forerunner of the NoSQL Database used at Google, or Megastore, a geographically replicated, consistent NoSQL-type datastore. Megastore uses the Paxos algorithm to ensure consistent reads and writes. [24]

The cloud service of Google utilises the Dremel Engine, a distributed SQL query engine, to perform complex queries over Big Data. [29] This engine uses two technologies to achieve the goal of 1 TB: Colossus, a large, parallel, distributed file system and ColumnIO, a storage format which arranges the data in a manner that makes it easier to query over this data. [24]

The Dremel Engine makes use of the Dremel Serving Tree algorithm to run the query on a distributed system. [29] The possible parallelisation of SQL-like queries is depending on the complexity of these queries. In most operations, the SQL query will be distributed to many workers (shards) and mixers. These different nodes will process the SQL query in parallel and are returning the result.

V. ENCRYPTED BIGQUERY COMMAND LINE INTERFACE

Google BigQuery offers a powerful asynchronous API to access the resources provided by Google. In addition, Google has released a beta client written in Python which is using encryption based on [17] called "Encrypted Big Query Command-Line Tool" (ebq). [30]

1This solution is only adequate if Big Data chunks are uploaded and the fragmentation is not too high.
To provide data for the CLI, the plaintext table data needs to be stored either as comma-separated values (CSV) or JavaScript Object Notation (JSON) file. The definition, which encryption should be used on which data, needs to be provided in a second scheme file. This extended table schema is provided by the user, where the extended schema is a modification of the BigQuery scheme. The unmodified ebq-client supports Paillier’s homomorphic encryption algorithm [31], as well as probabilistic, pseudonym and different searchword algorithms. [28] To support Order-Preserving encryption, the client has been modified and a new encryption scheme is implemented. The CLI is used as encryption proxy and is sorting the data, using “timsort”, a hybrid stable sorting algorithm, with a best case performance of $O(n)$, average and worst case performance of $O(n \log n)$. The plaintext will be encrypted using AES with CBC/PKCS5 Padding. The client uses a simple implementation as proof of concept. The encrypted data and the decimal order value will be written together to a column separated by a special character. In addition to for research purpose, the order is also written to a separate column.

All encrypted data is stored in a temporary file. If the data-encryption and -sorting is finished, the file will be uploaded by using the API of Google BigQuery. The private key will not be transmitted to the external source. BigQuery uses a RESTful API and the Transport-Layer- Security (TLS) protocol to communicate encrypted with the client. The packages sent to the API are lossless compressed with gzip using the deflate algorithm. By using the compression, the data transfer can be sped up by +50-75%, depending on the size and the quality of the data.

We have implemented Order-Preserving Encryption based on the mOPE Algorithm. Based on the modification, the ebq client is now capable of using a high range of different encryption algorithms including OPE for Big Data.

The in-depth analysis of the modified beta client in [28] has been investigated on different components of the client to detect possible impediments of the encryption. We have reviewed the resource and time consumption of uploading, query processing, sorting and encrypting. The analysis has proven that the bottle neck for the encrypted BigQuery client is the encryption of new data before uploading it to the external service. Due to the compression, the upload time for new data is relatively low, compared to the time consumption of the encryption. For sampling we used simulated credit card information with a sample size from $10^3$ to $10^7$ samples. Comparing the time consumption for ordering and encrypting the samples on the encryption proxy to uploading and preparing the data on Google BigQuery, has shown that the API runtime period is about 100 times faster than the proxy. These samples also have been tested with complex SELECT and ORDER BY statements. The response time for queries was in any test case less than 10 second, even when returning $10^6$ query results.

Considering Big Data, we have also evaluated that standard state of the art client laptop[1] can work with encrypted Big Data. We focused on the encryption as bottleneck for resource consumption. For this examination we have extracted the encryption method used in our modified ebq client and sampled it with random 16 digit integer values, simulating credit card numbers. Table I shows a linear correlation in the equivalent file size of the unencrypted data in order to the sample size as well as a linear correlation in time consumption for the encryption in order to the sample size. The sample scenario confirmed our expectation of extremely fast responses once the data is uploaded to the external system but also shows, that basic workstations can work with an extreme high amount of data in a reasonable time.

| Sample Size | Digits | Equivalent File Size | Time Consumption |
|-------------|--------|----------------------|------------------|
| $1.000$     | $10$   | $25.9$ kB            | $0.0034$ s       |
| $10.000$    | $10$   | $268.9$ kB           | $0.0214$ s       |
| $100.000$   | $10$   | $2.8$ MB             | $0.2035$ s       |
| $1.000.000$ | $10$   | $28.9$ MB            | $2.0432$ s       |
| $10.000.000$| $10$   | $298.9$ MB           | $21.7537$ s      |

VI. CONCLUSION, FUTURE WORK AND DISCUSSION

We demonstrated that it is possible to use external resources without decreasing the level of security more than the theoretically necessary minimum of Order-Preserving Encryption. With the imperative requirement of revealing the order of the encrypted data, it is possible to work with the data on the external resource, but to maintain the secrecy of private data. With the introduction of a new concept, which deports to work with encryption on an external resource and by using the modified encrypted BigQuery client, it is feasible to encrypt and sort Big Data using any symmetric encryption algorithm. We have also combined widely used algorithms and state of the art encryption to work with modern Infrastructure-as-a-Service environment. OPE is still a new technology and should be used with care but offers already a feasible way to protect confidentiality. Further work will focus on overcoming the remaining limitations, using the client as encryption proxy. We plan to implement recent algorithm to hide the user’s query distribution and by that making it even harder to reveal information besides the order.

With our solution it is possible to handle modern Big Data use cases. Even if, in first place, data is not considered as Big. If a system collecting timestamped GPS data produces a million records a day, it might not be Big Data. In three years, however, the system will have created a billion records. Data processing over a long period of time is important to detect the development or periodic trends. Often, the amount or the length back in time is important and will produce better results the more data sets are available. [24] This example shows, that a slower encryption but a fast analysis on the data by many clients is feasible and convenient for modern databases.

We have proposed different encryption algorithms which can be used with our concept besides Order-Preserving Encryption. Different data in a dataset does need different encryption algorithms depending on the projected queries and operations. This does have an impact on the design of the database scheme and can increases data security. With the modified ebq-client, the full range of algorithms and therefore operations is possible.

2The higher time consumption is caused by the asynchronous API of Google BigQuery. The client will send an asynchronous call to the GBQ API. Depending on the load of the API at the moment, the calls will be processed one by one.

3Intel Core i7-5600 4x2.60GHz; 16 GB RAM; Arch Linux (Kernel: 4.6.2); Python 2.7.11
Recent work by Mavroforakis et. al. [19] has revisited the Modular Order-Preserving Encryption (MOPE) Algorithm [23]. MOPE is slightly different to mOPE, but is also possible for a external database service to gain more information besides the order by observing the user’s queries. In [19] the author discusses three contributions to hide the user’s query distribution by mixing it with another distribution. The described methods are possible, but are not implemented yet in the proof of concept client of this work.

For high security needs, it is also possible to use Oblivious RAM (ORAM). ORAM is a technique that hides all information about which positions in an outsourced database are accessed by the client, by continually shuffling around and re-encrypting the data. [32], [33], [19]. Considering [19] ORAM is less efficient and the proposed solutions more sufficient for OPE.

REFERENCES
[1] Agrawal, Divyakant ; Abbadi, Amr E. ; Oot, Beng C. ; Das, Sudipto ; Elmore, Aaron J.: The Evolving Landscape of Data Management in the Cloud. In: Int. J. Comput. Sci. Eng. 7 (2012), März, Nr. 1, 2–16. http://dx.doi.org/10.1504/IJCSSE.2012.046177 – DOI 10.1504/IJCSSE.2012.046177. – ISSN 1742–7185
[2] Amazon: Amazon RDS. http://aws.amazon.com/rdss/, 2016. – [Online; Visited 21. Jun 2016]
[3] Brantner, Matthias ; Florescu, Daniela ; Graf, David ; Kossmann, Donald ; Kraska, Tim: Building a Database on S3. In: Proceedings of the 2008 ACM SIGMOD International Conference on Management of Data. New York, NY, USA : ACM, 2008 (SIGMOD ’08). – ISBN 978–1–60558–102–6, 251–264
[4] Curino, Carlo ; Jones, Evan P. C. ; Popa, Raluca A. ; Malviya, Nirmesh ; Wu, Eugene ; Madden, Sam ; Balakrishnan, Hari ; Zeldovich, Nickolai: Relational Cloud: A Database-as-a-Service for the Cloud. In: 5th Biennial Conference on Innovative Data Systems Research. CIDR (2011)
[5] Das, Sudipto ; Agrawal, Divyakant ; El Abbadi, Amr: ElastTra$S: An Elastic, Scalable, and Self-Managing Transactional Database for the Cloud. In: ACM Trans. Database Syst. 38 (2013), April, Nr. 1, 5:1–5:45. http://dx.doi.org/10.1145/2445583.2445588 – DOI 10.1145/2445583.2445588. – ISSN 0362–5915
[6] Google Inc.: Google Cloud SQL. https://cloud.google.com/products/cloud-sql, 2016. – [Online; Visited 21. Jun 2016]
[7] Microsoft: SQL Azure. http://www.windowsazure.com/en-us/develop/net/fundamentals/cloud-storage/, 2016. – [Online; Visited 21. Jun 2016]
[8] Hacıgümüş, Hakan ; Iyer, B. ; Mehirotwa, S.: Providing database as a service. In: Data Engineering, 2002. Proceedings. 18th International Conference on, 2002. – ISBN 1063–6382, 29–38
[9] Hacıgümüş, Hakan ; Iyer, Bala ; Li, Chen ; Mehirotwa, Sharad: Executing SQL over Encrypted Data in the Database-service-provider Model. In: Proceedings of the 2002 ACM SIGMOD International Conference on Management of Data. New York, NY, USA : ACM, 2002 (SIGMOD ’02). – ISBN 1–58113–497–5, 216–227
[10] Popa, Raluca A. ; Li, Frank H. ; Zeldovich, Nickolai: An Ideal Security Protocol for Order-Preserving Encryption. In: IEEE Symposium of Security and Privacy (2013)
[11] Agrawal, Rakesh ; Kierman, Jerry ; Srikant, Ramakrishnan ; Xu, Yirong: Order Preserving Encryption for Numeric Data. In: Proceedings of the 2004 ACM SIGMOD International Conference on Management of Data. New York, NY, USA : ACM, 2004 (SIGMOD ’04). – ISBN 1–58113–859–8, 563–574
[12] Ge, T. ; Zdonik, S.: Fast, Secure Encryption for Indexing in a Column-Oriented DBMS. In: 2007 IEEE 23rd International Conference on Data Engineering, 2007. – ISBN 1063–6382, S. 676–685
[13] Kadhem, Hasan ; Amagasa, Toshiyuki ; Kitagawa, Hiroyuki: A Secure and Efficient Order Preserving Encryption Scheme for Relational Databases. In: Conference: KMIS 2010 - Proceedings of the International Conference on Knowledge Management and Information Sharing, Valencia, Spain (2010)
[14] Lee, Seungmin ; Park, Tae-Jun ; Lee, Donghyek ; Nam, Taekyong ; Kim, Seungho: Chaotic Order Preserving Encryption for Efficient and Secure Queries on Databases. In: IEICE Transactions on Information and Systems E92.D (2009), Nr. 11, S. 2207–2217. http://dx.doi.org/10.1587/transinf.E92.D.2207
[15] Liu, D. ; Wang, S.: Programmable Order-Preserving Secure Index for Encrypted Database Query. In: Cloud Computing (CLOUD), 2012 IEEE 5th International Conference on, 2012. – ISBN 2159–6182, S. 502–509
[16] Liu, Dongxi ; Wang, Shenhui: Nonlinear order preserving index for encrypted database query in service cloud environments. In: Concurrency and Computation: Practice and Experience 25 (2013), Nr. 13, 1967–1984. http://dx.doi.org/10.1002/cpe.2992. – DOI 10.1002/cpe.2992. – ISSN 1532–0634
[17] Popa, Raluca A. ; Redfield, Catherine M. ; Zeldovich, Nickolai ; Balakrishnan, Hari: CryptDB: Protecting Confidentiality with Encrypted Query Processing. In: Proceedings of the Twenty-Third ACM Symposium on Operating Systems Principles. New York, NY, USA : ACM, 2011 (SOSP 11). – ISBN 978–1–4503–0977–6, 85–100
[18] Liangliang, Xiao ; I-Ling, Yen ; Dung, T. H.: Extending Order Preserving Encryption for Multi-User Systems. In: Cryptology ePrint Archive, Report 2012/192 (2012)
[19] Mavroforakis, Charalampos ; Chenette, Nathan ; O’Neill, Adam ; Kollios, George ; Canetti, Ran: Modular Order-Preserving Encryption, Revisited. In: Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data. New York, NY, USA : ACM, 2015 (SIGMOD ’15). – ISBN 978–1–4503–2758–9, 763–777
[20] Gentry, Craig: Fully Homomorphic Encryption Using Ideal Lattices. In: Proceedings of the Forty-first Annual ACM Symposium on Theory of Computing. New York, NY, USA : ACM, 2009 (STOC ’09). – ISBN 978–1–60558–506–2, 169–178
[21] In: Gentry, Craig ; Halevi, Shai ; Smart, Nigel P.: Homomorphic Evaluation of the AES Circuit. Berlin, Heidelberg : Springer Berlin Heidelberg, 2012. – ISBN 978–3–642–32000–5, 850–867
[22] Boldyreva, Alexandra ; Chenette, Nathan ; Lee, Younho ; O’Neill, Adam: Order-Preserving Symmetric Encryption. In: Proceedings of the 28th Annual International Conference on Advances in Cryptology: The Theory and Applications of Cryptographic Techniques, Berlin, Heidelberg : Springer-Verlag, 2009 (EUROCRYPT ’09). – ISBN 978–3–642–01000–2, 224–241
[23] Boldyreva, Alexandra ; Chenette, Nathan ; O’Neill, Adam: Order-preserving Encryption Revisited: Improved Security Analysis and Alternative Solutions. In: Proceedings of the 31st Annual Conference on Advances in Cryptology, Berlin, Heidelberg : Springer-Verlag, 2011 (CRYPTO ’11). – ISBN 978–3–642–22791–2, 578–595
[24] Tigan, Jordan ; Naidu, Siddartha: Google BigQuery Analytics. Wiley, 2014
[25] Yin, S. ; Kaynak, O.: Big Data for Modern Industry: Challenges and Trends [Point of View]. In: Proceedings of the IEEE 103 (2015), Feb, Nr. 2, S. 143–146. http://dx.doi.org/10.1109/JPROC.2015.2383958. – DOI 10.1109/JPROC.2015.2383958. – ISSN 0018–9219
[26] Carceller, Rick: Scalable SQL and NoSQL Data Stores. In: SIGMOD Rec. (2011)
[27] Dean, Jeffrey ; Ghemawat, Sanjay: MapReduce: Simplified Data Processing on Large Clusters. In: Commun. ACM (2008)
[28] Schindler, Timo: Secure Parallel Processing of Big Data Using Order-Preserving Encryption on Google BigQuery, OTH Regensburg, Diplomarbeit, 2016
[29] Melnik, Sergey ; Guibaud, Andrey ; Long, Jing J.; Romero, Geoffrey ; Shivakumar, Shiva ; Tolton, Matt ; Vasilakis, Theo: Dremel: Interactive Analysis of Web-scale Datasets. In: Proc. VLDB Endow. (2010)
[30] Google Inc.: encrypted-bigquery-client. https://github.com/google/encrypted-bigquery-client, 2016.
[31] PAIILLIER, Pascal: Public-Key Cryptosystems Based on Composite Degree Residuosity Classes. In: Advances in Cryptology - EUROCRYPT 99 (1999)

[32] STEFANOV, Emil ; DIJK, Marten van ; SHI, Elaine ; FLETCHER, Christopher ; REN, Ling ; YU, Xiangyao ; DEVADAS, Srinivas: Path ORAM: An Extremely Simple Oblivious RAM Protocol. In: Proceedings of the 2013 ACM SIGSAC Conference on Computer & Information Security. New York, NY, USA : ACM, 2013 (CCS '13). – ISBN 978-1-4503-2477-9, 299–310

[33] GOLDBREICH, Oded ; OSTROVSKY, Rafail: Software Protection and Simulation on Oblivious RAMs. In: J. ACM 43 (1996), Mai, Nr. 3, 431–473. [http://dx.doi.org/10.1145/233551.233553] – DOI 10.1145/233551.233553. – ISSN 0004-5411