

Computing on Masked Data: a High Performance Method for Improving Big Data Veracity

Jeremy Kepner, Vijay Gadepally, Pete Michaleas, Nabil Schear, Mayank Varia, Arkady Yerukhimovich, Robert K. Cunningham
MIT Lincoln Laboratory, Lexington, MA, U.S.A.

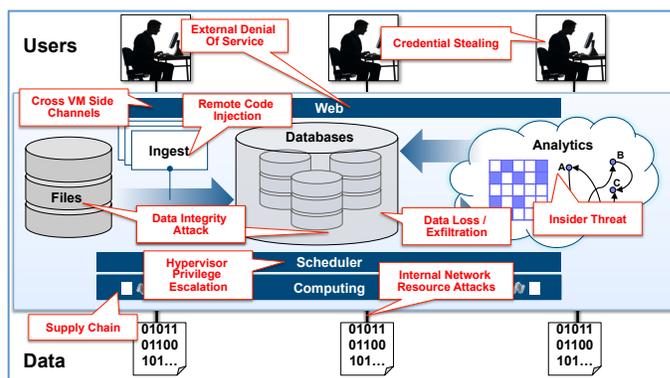
Abstract— The growing gap between data and users calls for innovative tools that address the challenges faced by big data volume, velocity and variety. Along with these standard three V’s of big data, an emerging fourth “V” is veracity, which addresses the confidentiality, integrity, and availability of the data. Traditional cryptographic techniques that ensure the veracity of data can have overheads that are too large to apply to big data. This work introduces a new technique called Computing on Masked Data (CMD), which improves data veracity by allowing computations to be performed directly on masked data and ensuring that only authorized recipients can unmask the data. Using the sparse linear algebra of associative arrays, CMD can be performed with significantly less overhead than other approaches while still supporting a wide range of linear algebraic operations on the masked data. Databases with strong support of sparse operations, such as SciDB or Apache Accumulo, are ideally suited to this technique. Examples are shown for the application of CMD to a complex DNA matching algorithm and to database operations over social media data.

Keywords—Big Data; Accumulo; D4M; Security; Encryption

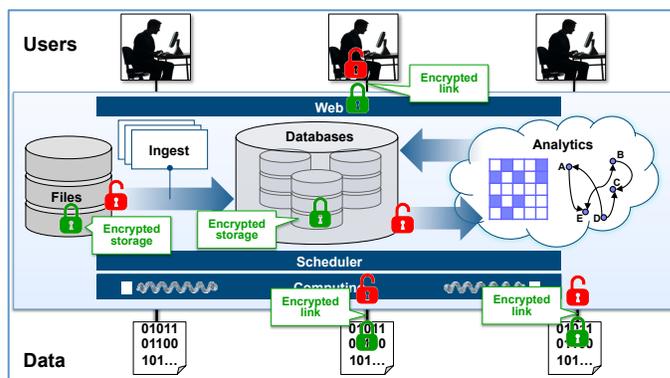
I. INTRODUCTION

Big data and big data solutions are commonly characterized by the three V’s: volume, velocity, and variety [Laney 2001]. The 17 member agencies of the US intelligence community face many similar issues in transforming their big data into actionable solutions for their users. Led by the National Security Agency, a Common Big Data Architecture (CBDA) was developed based on the Google Big Table design [Chang 2008] to help address these issues and is now in wide use. The centerpiece of the CBDA is the Apache Accumulo database (accumulo.apache.org) and its D4M (aka NuWave) schema [Kepner 2013a]. The CBDA connects users with data using a range of technologies: file systems, ingest processes, databases, data analytics, web services, scheduling, and elastic computing (Figure 1). Increasingly, big data solutions must address the confidentiality, integrity and availability of their data leading to the designation of a fourth V: veracity.

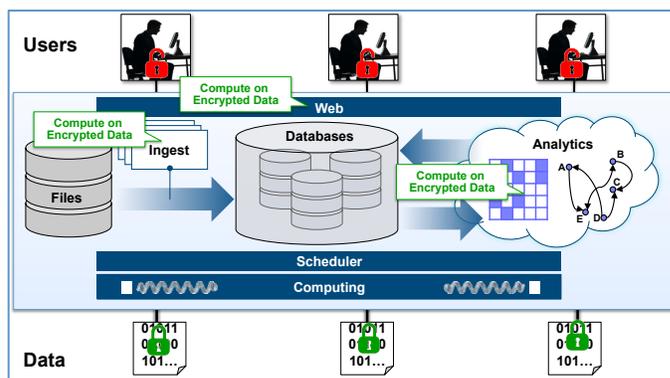
There are many veracity challenges in a big data system (see Figure 1a): external denial of service, credential stealing, cross virtual machine (VM) side channels, VM hypervisor privilege escalation, remote code injection, data integrity attacks, data loss/exfiltration, insider threats, internal network resource attacks, and supply chain attacks [Evans 2013]. These attacks threaten the availability, confidentiality, and the integrity of both the original data and the analytic results.



(a) big data veracity: challenges



(b) big data veracity: current approaches



(c) big data veracity: vision

Figure 1. The Common Big Data Architecture connects diverse users with diverse data. Shown are big data veracity challenges (a), current approaches (b), and longer term vision (c).

This work is sponsored by the Assistant Secretary of Defense for Research and Engineering under Air Force Contract #FA8721-05-C-0002. Opinions, interpretations, recommendations and conclusions are those of the authors and are not necessarily endorsed by the United States Government. U.S. Government work not protected by U.S. copyright.

These attacks threaten to degrade the availability of the big data system, compromise the confidentiality of the data and analytics used, and violate the integrity of both the original data and the analytic results. There are several approaches to mitigating these veracity challenges. Data centric veracity protections are particularly useful for preserving the confidentiality of the data. Typical defenses of this type include (see Figure 1b): encrypting the links between users and the big data system, encrypting the links between the data sources and the big data system, encrypting the data in the file system, and encrypting data in the database when it is at rest. These approaches are all significant steps forward in improving the veracity of a big data system. However, all of these approaches require that the data be decrypted for it to be used inside the big data system, which requires that the keys to the data be available to the big data system thus exposing the data to any attacker able to breach the boundaries of the system.

One vision (Figure 1c) for a big data system is to have data sources encrypt data prior to transmitting it to the system, have the big data system operate on the data in encrypted form, and only allow authorized users the keys to decrypt the answer for their specific result. Such a system makes the underlying big data technologies oblivious to the details of the data and would go a long way towards mitigating the big data veracity challenges described above. As a result, the data and processing can be outsourced to an untrusted cloud while preserving the confidentiality of the data and results.

Our Computing on Masked Data (CMD) system is a first step in this direction allowing for basic computations on encrypted data to enable a rich class of analytics. CMD combines efficient cryptographic encryption methods with an associative array representation of big data to enable a low computation cost approach to both computation and query while revealing only a small amount of information about the underlying data. The overhead of CMD is sufficiently low ($\sim 2x$) to make it feasible for big data systems. Currently, all big data systems must operate on their data in the clear. CMD raises the bar by enabling some important computations on encrypted data while not dramatically increasing the computing resources required to perform those operations.

The outline of the rest of this paper is as follows. Section II gives a brief introduction to the relevant cryptographic tools. Section III describes the mathematics of associative arrays that underpin CMD and the D4M schema that is used to transform big data into associative arrays. Section IV describes the CMD system and how it can be integrated with the standard big data schemas. Section V presents the results of using CMD for analyses on bioinformatics and social media data. Section VI presents our conclusions and plans for future work.

II. RELEVANT CRYPTOGRAPHIC TOOLS

There are several cryptographic tools that one could use to build a system like CMD. First, fully homomorphic encryption (FHE) allows for arbitrary analytic computations to be performed on encrypted data without decrypting it and while preserving its semantic security (i.e., no information about the data is leaked other than its length). FHE has been an active topic of research since its discovery [Gentry 2009]. Nevertheless, the best currently available schemes [Perl 2011,

Halevi 2014] have an overhead of 10^5 or more, making them too slow for use in practical big data systems.

If one is willing to allow a small amount of information about the encrypted data to be revealed, a much more efficient alternative to using FHE is to design protocols that leverage more traditional cryptographic techniques to carry out queries on encrypted data. One example of such a protocol is CryptDB [Papa 2011], which constructs a practical database system capable of handling most types of SQL queries on encrypted data. It uses deterministic encryption (DET), which always encrypts the same data to the same ciphertext, to enable equality queries; order-preserving encryption (OPE), which encrypts data in a way that preserves the original order of the data, to enable range queries; and additively homomorphic encryption (HOM+), which enables summing values directly on encrypted data, to perform basic analytics. Several other protocols achieving alternative trade-offs between leakage and efficiency have been proposed by e.g. [Cash 2013, Raykova 2012, Pal 2012]. Additional solutions are also possible using techniques for secure multi-party computation [Yao 1982, Ben-Or 1988] but these require further improvement to achieve the required performance.

CMD provides another important technology to this space of solutions (Figure 2) that trade off computational overhead and data leakage and is the first to focus on big data systems.

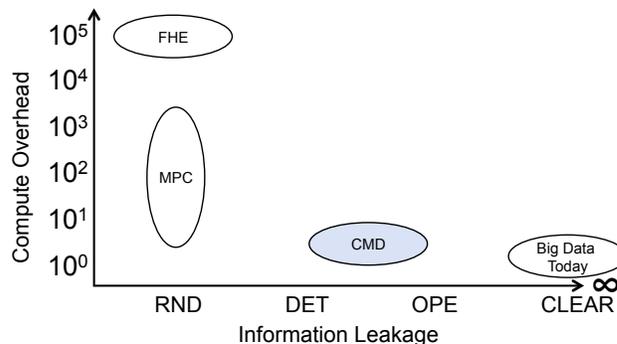


Figure 2. Trade space showing compute overhead versus information leakage for different approaches. RND is a semantically secure encryption scheme (i.e., it leaks no other information other than the length of the message). DET deterministically encrypts each input into exactly one output thus leaking equality information. OPE encrypts the data in a way that preserves (and thus reveals) the relative order of the all inputs. CLEAR has no encryption and leaks all information to someone who has access to the data. FHE is fully homomorphic encryption. MPC is multi-party computation. CMD most often uses DET and OPE.

III. ASSOCIATIVE ARRAYS

CMD operates by working on a mathematical object called an *associative array* that combines features of sparse matrices and triple store databases (such as Apache Accumulo).

Associations between multidimensional entities (tuples) using number/string keys and number/string values can be stored in associative arrays. An implementation of associative arrays can be found in the D4M software package (d4m.mit.edu)[Kepner 2012]. In two dimensions, A D4M associative array entry might be

$A('alice', 'bob') = 'cited'$
or $A('alice', 'bob') = 47.0$

The above tuples have a 1-to-1 correspondence with their triple store representations

```
('alice ', 'bob ', 'cited ')
or ('alice ', 'bob ', 47.0)
```

Associative arrays can represent complex relationships in either a sparse matrix or a graph form (see Figure 3). Thus, associative arrays are a natural data structure for performing both matrix and graph algorithms. Such algorithms are the foundation of many complex analytics [Kepner 2011].

Constructing complex, composable query operations can be expressed using simple array indexing of the associative array keys and values, which themselves return associative arrays

```
A('alice ', :)      alice row
A('alice bob ', :)  alice and bob rows
A('al* ', :)        rows beginning with al
A('alice : bob ', :) rows alice to bob
```

The composability of associative arrays stems from the ability to define fundamental mathematical operations whose results are also associative arrays. Given two associative arrays A and B, the results of all the following operations will also be associative arrays

```
A + B   A - B   A & B   A|B   A*B
```

Associative array composability can be further grounded in an axiomatic definition for associative arrays in terms of semi-modules over semi-rings [Kepner 2013b].

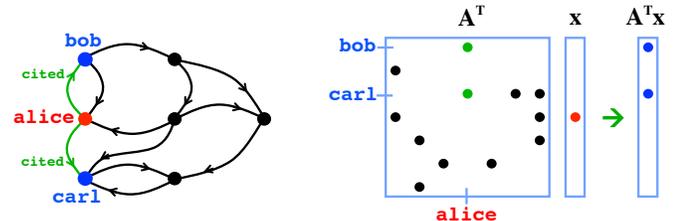


Figure 3. A graph describing the relationship between **alice**, **bob**, and **carl** (left). A sparse associative array A captures the same relationships (right). The fundamental operation of graphs is finding neighbors from a vertex (breadth first search). The fundamental operation of linear algebra is vector matrix multiply. D4M associative arrays make these two operations identical. Algorithm developers can use both graph and linear algebra to perform complex operations.

Associative arrays are a critical part of D4M, which has proven useful in a variety of domains (e.g., documents, network logs, social media, and DNA sequences). Measurements using D4M indicate these algorithms can be implemented with a tenfold decrease in coding effort when compared to standard approaches [Kepner 2012]. For example, the D4M schema (aka NuWave) used extensively by the Apache Accumulo community allows diverse data to be quickly ingested and fully indexed using a handful of tables. A feature of the D4M schema is that the data obeys the algebra of associative arrays.

The top part of Figure 4 demonstrates an example of how D4M transforms network log data into an associative array. The raw network traffic logs are collected in a dense tabular form that is made sparse using the same approaches found in the standard D4M schema (i.e., each dense table column and value are appended to make a new sparse table column). CMD exploits this same sparse structure to work on associative arrays that have been encrypted in various forms.

IV. COMPUTING ON MASKED DATA SYSTEM

The standard CMD use case is as follows. First, users transform their data into associative arrays following the D4M schema (as described in Section III). Then, the components of the associative array’s rows, columns, and values are masked using different encryption schemes; this process induces a permutation on rows and columns as they are restructured in lexicographic order by their masks. At this point the masked data structure can optionally be distributed to a system in the encrypted form. Next, algebraic operations are performed on the masked associative arrays. Finally, the results are collected by the user and unmasked.

The bottom part of Figure 4 demonstrates some of the masks that can be used in CMD: DET for the rows (since range queries on rows aren’t required), OPE for the columns (which allows for range queries), and RND (a semantically secure encryption scheme) for the values. Another option would be to use an additively homomorphic encryption scheme (HOM+) if the values require summing.

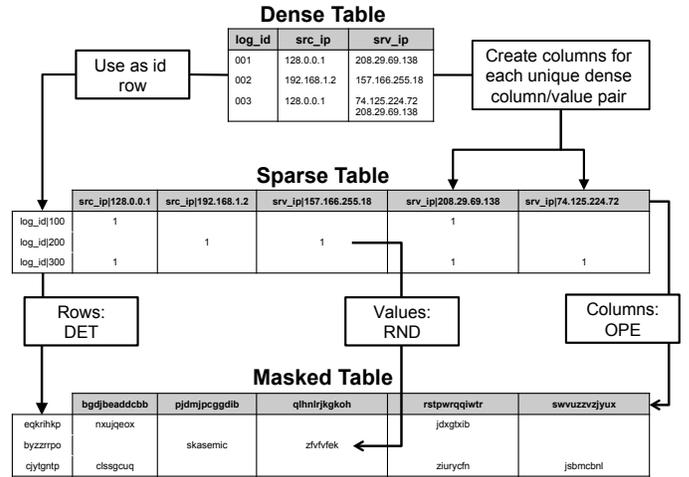


Figure 4. Masking network data records. Dense data is made sparse using the D4M schema that is widely used in the Apache Accumulo community. Dense table column names and values are appended to make columns in the sparse table, which moves most of the semantic content into the rows and columns. The sparse table is then masked using a variety of encryption schemes depending upon the desired application. The rows are masked using DET, the columns are masked using OPE, and the values are masked using RND.

DET and OPE induce a random permutation on the rows and columns (resp.) of the sparse matrix, but the overall structure of the matrix is preserved. Linear algebra and the algebra of associative arrays are invariant to such permutations (i.e., linear algebraic operations on the masked table will have the same effect as linear algebraic operations on the unmasked sparse table). This is the key concept of CMD, and gives it the ability to perform a wide range of operations on masked data.

Note that CMD may leak the permuted sparse structure of the table. However, determining whether this corresponds to a known unpermuted structure requires solving the graph isomorphism problem, which is not believed to have a generic efficient solution.

Computing the `src_ip` to `srv_ip` graph from the network log data shown in Figure 4 is accomplished by matrix

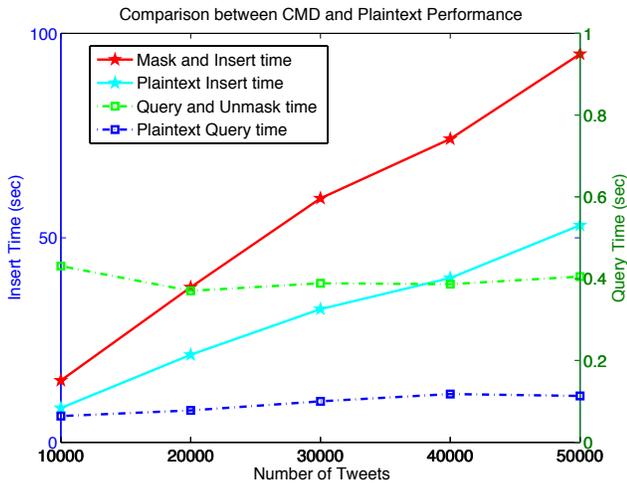


Figure 7. Performance of CMD system on a varying number of Tweets. The Left Y-axis corresponds to the time taken for Inserting data. The red line corresponds to the CMD insert operation which includes time for masking and inserting. The cyan line corresponds to just inserting plaintext. The red and cyan lines show the relative performance between CMD and plaintext and corresponds to an overhead less than 2x. The right Y-axis corresponds to the time taken for querying for data. As querying in Accumulo is a constant time operation, both lines are relatively flat. The difference between the green and blue dashed lines correspond to the overhead incurred in masking the query and unmasking the result associative array.

Figure 7 shows the performance obtained by the CMD system for a varying data size from 10,000 tweets to 50,000 tweets. The Twitter data inserted is represented by the D4M schema. The insert times include time taken for inserting (and masking) the data stored in all the tables required by the D4M Schema. These operations are dominated by the database insert and query time. The increase in insert and query time is due to the increase in the data size that comes from padding the data to 16 bytes blocks for encryption and base64 encoding. This doubles the size of the data and results in a doubling of insert and query time. This is a reasonable tradeoff for many big data systems in exchange for no longer having data in the clear.

VI. SUMMARY & FUTURE WORK

CMD is a novel approach that increases big data veracity while allowing a wide range of computations and queries to be performed with low overhead. The encryption schemes used in CMD can be tailored to the application: semantically secure, deterministic, order preserving, and homomorphic encryption can be used in complementary fashion to provide the best overall application solution. Through continued dialog between big data application designers and cryptographers, further improvements can fine-tune the balance between performance and veracity of big data systems.

A prototype CMD was implemented with DET by adding four functions to the existing D4M library. Using this implementation, CMD was demonstrated on a DNA sequence matching problem and the performance met the 2x performance goal. The CMD system was also demonstrated

with a social media dataset that also met the performance goals. Future improvements to the prototype include expanding and improving the encryption schemes to use the full set developed in CryptDB and using direct procedure calls to reduce the overhead of the mask and unmask functions.

REFERENCES

- [Ben-Or 1988] M. Ben-Or, S. Goldwasser, & A. Wigderson, "Completeness Theorems for Non-Cryptographic Fault-Tolerant Distributed Computation (Extended Abstract)," STOC 1988
- [Cash 2013] D. Cash, S. Jarecki, C.S. Jutla, H. Krawczyk, M.-C. Rosu, & M. Steiner, "Highly-Scalable Searchable Symmetric Encryption with Support for Boolean Queries," CRYPTO 2013
- [Chang 2008] F. Chang, J. Dean, S. Ghemawat, W. Hsieh, D. Wallach, M. Burrows, T. Chandra, A. Fikes, & R. Gruber, "Bigtable: A Distributed Storage System for Structured Data," ACM Transactions on Computer Systems, Volume 26 Issue 2, Jun 2008
- [Evans 2013] E. Evans & R. Grossman, "Cyber Security and Reliability in a Digital Cloud," U.S. Department of Defense Science Board Study, Jan 2013
- [FIPS 197] "Announcing the ADVANCED ENCRYPTION STANDARD (AES)," Federal Information Processing Standards Publication 197, United States National Institute of Standards and Technology (NIST), November 26, 2001
- [Gentry 2009] C. Gentry, "Fully Homomorphic Encryption Using Ideal Lattices," 41st ACM Symposium on Theory of Computing (STOC), 2009
- [Halevi 2003] S. Halevi and P. Rogaway, "A Tweakable Enciphering Mode." In: CRYPTO, D. Boneh (ed.), LNCS, vol. 2729, pp. 482-499, Springer, 2003
- [Halevi 2014] S. Halevi & V. Shoup, "Algorithms in HELib." Cryptology ePrint Archive, Report 2014/106. <http://eprint.iacr.org/2014/106>
- [Kepner 2011] J. Kepner & J. Gilbert, "Graph Algorithms in the Language of Linear Algebra," SIAM Press, Philadelphia, 2011
- [Kepner 2012] J. Kepner, W. Arcand, W. Bergeron, N. Bliss, R. Bond, C. Byun, G. Condon, K. Gregson, M. Hubbell, J. Kurz, A. McCabe, P. Michaleas, A. Prout, A. Reuther, A. Rosa & C. Yee, "Dynamic Distributed Dimensional Data Model (D4M) Database and Computation System," ICASSP, Mar 25-30, 2012
- [Kepner 2013a] J. Kepner, C. Anderson, W. Arcand, D. Bestor, W. Bergeron, C. Byun, M. Hubbell, P. Michaleas, J. Mullen, D. O'Gwynn, A. Prout, A. Reuther, A. Rosa, & C. Yee, "D4M 2.0 Schema: A General Purpose High Performance Schema for the Accumulo Database," IEEE HPEC, Sep 10-12, 2013
- [Kepner 2013b] J. Kepner & J. Chaidez, "The Abstract Algebra of Big Data," Union College Mathematics Conference, Oct 19, 2013
- [Kepner 2013c] J. Kepner, D. Ricke, & D. Hutchinson, "Taming Biological Big Data with D4M," Lincoln Laboratory Journal, Vol 20, No 1, 2013
- [Laney 2001] D. Laney, "3D Data Management: Controlling Data Volume, Velocity and Variety," Gartner, 6 Feb 2001
- [Pal 2012] Pal, P., Lauer, G., Khoury, J., Hoff, N., Loyall, J.: P3S: A privacy preserving publish-subscribe middleware. In: Narasimhan, P., Triantafillou, P. (eds.) Middleware 2012. LNCS, vol. 7662, pp. 476-495. Springer, Heidelberg, 2012
- [Perl 2011] H. Perl, M. Brenner, & M. Smith, "Poster: an implementation of the fully homomorphic Smart-Vercauteren crypto-system." CCS 2011
- [Popa 2011] R.A. Popa, C.M.S. Redfield, N. Zeldovich, & H. Balakrishnan, "CryptDB: Protecting Confidentiality with Encrypted Query Processing," Proceedings of the 23rd ACM Symposium on Operating Systems Principles (SOSP), Cascais, Portugal, Oct 2011
- [Raykova 2012] M. Raykova, A. Cui, B. Vo, B. Liu, T. Malkin, S.M. Bellare, & S.J. Stolfo, "Usable, Secure, Private Search," IEEE Security & Privacy 10(5), 2012
- [Yao 1982] A.C.-C. Yao, "Protocols for Secure Computations (Extended Abstract)," FOCS 1982