# BigSecret: A Secure Data Management Framework for Key-Value Stores

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## **Motivation**

- Increased network traffic, and number of users in the last decade
  - Simultaneously millions of users want to surf on popular web sites, e.g. Facebook, Twitter, Amazon
- Traditional databases may cause bottlenecks
  - ACID properties may not be needed
  - Some applications may tolerate inconsistencies in the data
  - A user wouldn't wait too much for a web page to open
- Retrieving data should be fast!



## **Motivation**

- Many companies have started adopting and providing Key-Value store solutions, e.g. Amazon's SimpleDB, Google's AppEngine
  - Very fast data retrieval and sending
  - Scalable
  - Allows dynamic data structure
- In a Key-Value store, data consists of a Key and Value pairing
  - Both are uninterpreted array of bytes
  - Stored based on some rules
    - Some may store in sorted order
    - Some may store using hash functions



## **Motivation**

- A Data Owner can outsource data to any number of public cloud providers
  - May also use its own cloud infrastructure, i.e. private cloud
- When public, sensitive information needs to be protected
- Securing data and providing efficient querying mechanisms is though



## Aim

- Provide scalable, efficient and secure solutions to outsource Key-Value data
- Utilize any existing cloud infrastructures to
  - Improve performance
  - Reduce the overall monetary cost
  - Reduce the overall sensitive data disclosure



## **Overview of the Solution: BigSecret**



#### Client - n

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## Outline

- How do we share data and workload on all providers?
  - Monetary metrics
  - Security metrics
  - Performance metrics
  - Heuristic solution
- How do we store data in encrypted form?
  - Transformation of data
  - Transformation of queries
- Experiments



- Given:
  - A dataset of Key-Value pairs,  $\ensuremath{\mathcal{D}}$
  - A workload on the dataset,  ${\cal Q}$
  - A set of providers,  ${\cal P}$
- First, partition workload over the providers such that
  - The total execution time of the workload is minimized
  - The total amount of monetary cost from cloud usage is below a limit
  - Expected amount of sensitive data disclosure is below a limit



- Second, partition data based on queries
  - All Key-Value pairs needed to answer a query is given to that provider





- Each provider  $P_i$  is given:
  - Partitioned workload  $Q_{P_i}$
  - Partitioned dataset  $\mathcal{D}_{P_i}$
- Total monetary cost of a workload  $Q_{P_i}$  on the provider  $P_i$  is:

$$t(\mathcal{Q}_{P_i}, P_i) := s(\mathcal{D}_{P_i}, P_i) + \sum_{q \in \mathcal{Q}_{P_i}} f(q) \times c(q, P_i)$$

• Total monetary cost of the partitioned workload  $Q_{P_1}, \ldots, Q_{P_k}$ :

 $- \sum t(\mathcal{Q}_{P_i}, P_i) \le C_{cost}$ 



- Expected number of sensitive Key-Value entries in  $\mathcal{D}_{P_i}$  is represented as  $sens(\mathcal{D}_{P_i})$
- Total expected disclosure:



• Expected execution time of a workload  $Q_{P_i}$ on  $P_i$  $r(Q_{P_i}, P_i) := \sum_{q \in Q_{P_i}} f(q) \times r(q, P_i)$ 

$$- r(q, P_i) := \frac{io(q)}{pow(P_i)}$$

• Minimize the total execution time:

- 
$$OptRun(\mathcal{Q}_{P_1},\ldots,\mathcal{Q}_{P_k}) := \sum_{P_i\in\mathcal{P}} r(\mathcal{Q}_{P_i},P_i)$$

 We call this particular partitioning problem over a set of providers as Multi-Cloud Partitioning Problem (MCPP), which is proven to be NP-Hard

#### Heuristic Solution to MCPP

- We approach the problem using Hill-Climbing technique
- First assign each query to a provider so that the initial constraints are met
- Then, iterate over each query and check
  - Better performance can be achieved
  - Constraints are still met
- Finish when no further improvements can be made



## **Background - HBase**

- Apache's open source Key-Value store implementation, designed after Google's BigTable
- Key consists of four parts:
  - row-key (row)
  - family (fam)
  - qualifier (qua)
  - timestamp (ts)
- Provides 4 operations:
  - Put, Get, Delete, and Scan



### **Data Transformation**

 Data is transformed into encrypted form using "Encryption Models"

	Model-1	Model-2	Model-3
row	Map(row)	H(row)	H(row)
fam	Map(fam)	H(fam)	0
qua	$Map(qua) \  E(KEY)$	$H(qua) \  E(KEY)$	E(KEY)
ts	Map(ts)	H(ts)	1
val	E(val)	E(val)	E(val)



#### **Query Translation**

- Given a Put query, translation for Model-2:
  - put("Jake", "personal", "height", "170cm", 1)
  - put(H("Jake"), H("personal"), H("height")||E(KEY), E("170cm"), H(1))
  - KEY = "Jakepersonalheight1"
- Given a Get query, translation for Model-2:
  - get("Jake", 0, ∞, "personal")
  - get(H("Jake"), 0,  $\infty$ , H("personal"))



#### **Experiments**

- Performed experiments using Yahoo! Cloud Serving Benchmark
- Created tables consisting of 1,2,4,8,16, and 32 Millions of rows
  - Each row has 10 Key-Value entries of 100B
- Created 3 different workloads
  - 1K queries for single-cloud experiments
  - 100K queries for multi-cloud experiments

	Workload-1	Workload-2	Workload-3
<b>Put</b> (%)	5	95	25
Get (%)	95	5	25
Scan (%)	0	0	50



## **Single-Cloud Experiments**





## **Single-Cloud Experiments**



## **Single-Cloud Experiments**



Workload - 3



## **Multi-Cloud Experiments**

- Same cluster is used with two different settings:
  - Provider-1: Plaintext storage,  $w_{P_1}$  is 1
  - Provider-2: Uses Model-2,  $w_{P_2}$  is 0.7
- Both have the same pricing policies
  - Amazon S3, EC2, and EMR pricing
- Monetary cost constraint varies between \$700 and \$3700
- All data is assumed to be sensitive



## **Multi-Cloud Experiments**



Workload - 3



#### Conclusion

- We proposed efficient and secure storage techniques, specially designed for Key-Value stores
- We formalized how to partition data and workload on a multi-cloud setup with monetary, sensitivity disclosure, and performance constraints
- We implemented BigSecret on Hbase, and evaluated the performance





- We plan to add support for other Key-Value stores
- BigSecret will be open-source





## Thank You



