

# Private Data Indexes for Selective Access to Outsourced Data

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# Motivation (1)

- The management of large amount of sensitive information is quite expensive
  - Database outsourcing is becoming increasingly popular (Database As a Service) [Hacigümüş et al., SIGMOD 2002]
    - + significant cost savings and service benefits
    - + promises higher availability and more effective disaster protection than in-house operations
    - sensitive data are not under the data owner's control
- ⇒ data encryption provides both integrity and confidentiality

## Motivation (2)

- The storage server can be **honest-but-curious**
- The server cannot decrypt the data for **executing queries**
  - ⇒ **indexes** can be associated with encrypted data to allow the server to execute queries on them
- The data owner may want to provide **different data views** to different users
  - ⇒ **selective encryption** uses different keys for different portions of the data
- The **combination** of the two solutions may open the door to **inferences** by users

# Our contributions

- Characterize the **exposure** of confidential information due to indexes and access control enforcement
- Define a novel **index function**, depending on plaintext values and access control restrictions, that
  - supports efficient query evaluation
  - protects against inference exposure
- **Translate queries** formulated on the plaintext relation into equivalent queries on the encrypted relation using indexes

# Encrypted relation

- Symmetric encryption is applied at the tuple-level
- The encrypted version of relation  $r$  over schema  $R(A_1, \dots, A_n)$  is a relation  $r^e$  over schema  $R^e(\underline{tid}, etuple, I_1, \dots, I_l)$ :
  - $tid$ : numerical attribute acting as primary key
  - $etuple$ : ciphertext resulting from the encryption of a tuple
  - $I_i, i=1, \dots, l$ : index over attribute  $A_{j_i} \in R$

	Id	City	Year	Sales
$t_1$	001	NY	2010	600
$t_2$	002	Rome	2010	700
$t_3$	003	Rome	2011	600
$t_4$	004	NY	2011	700
$t_5$	005	Oslo	2011	700

tid	etuple	$I_c$	$I_y$	$I_s$
1	$\alpha$	$t(NY)$	$t(2010)$	$t(600)$
2	$\beta$	$t(Rome)$	$t(2010)$	$t(700)$
3	$\gamma$	$t(Rome)$	$t(2011)$	$t(600)$
4	$\delta$	$t(NY)$	$t(2011)$	$t(700)$
5	$\epsilon$	$t(Oslo)$	$t(2011)$	$t(700)$

# Indexing techniques

- **Direct index** (e.g., [Damiani et al., CCS 2003])  
each plaintext value is mapped to a different index value and viceversa
- **Flattened index** (e.g., [Wang and Lakshmanan, VLDB 2006])  
each plaintext value is mapped to a set of index values and each index value corresponds to a unique plaintext value
- **Bucket/hash-based index** (e.g., [Hacigümüş et al., SIGMOD 2002; Damiani et al., CCS 2003])  
different plaintext values are mapped to the same index value

# User knowledge

Each user knows the:

- index functions used to define indexes in  $R^e$
- plaintext tuples that she is authorized to access
- encrypted relation  $r^e$  in its entirety

		SHOPS			
	acl	Id	City	Year	Sales
$t_1$	A	001	NY	2010	600
$t_2$	A,B	002	Rome	2010	700
$t_3$	B	003	Rome	2011	600
$t_4$	A,C	004	NY	2011	700
$t_5$	C	005	Oslo	2011	700

		SHOPS <sup>e</sup>			
	tid	tuple	I <sub>c</sub>	I <sub>y</sub>	I <sub>s</sub>
1	$\alpha$	$i(\text{NY})$	$i(2010)$	$i(600)$	
2	$\beta$	$i(\text{Rome})$	$i(2010)$	$i(700)$	
3	$\gamma$	$i(\text{Rome})$	$i(2011)$	$i(600)$	
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$t_3$	B	003	Rome	2011	600
$t_4$	A,C				
$t_5$	C				

		SHOPS <sup>e</sup>			
	tid	tuple	I <sub>c</sub>	I <sub>y</sub>	I <sub>s</sub>
1	$\alpha$	$\iota(\text{NY})$	$\iota(2010)$	$\iota(600)$	
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# Exposure risk: Direct index (1)

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- Plaintext values are always represented by the same index value and viceversa
  - ⇒ cells having the same plaintext values are exposed

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5	$\epsilon$	$\iota(\text{Oslo})$	$\iota(2011)$	$\iota(700)$

# Exposure risk: Direct index (2)

- Each user knows index function  $\iota$ 
  - $\Rightarrow$  all index-plaintext value correspondences are exposed to brute-force attacks
  - $\Rightarrow$  the whole outsourced relation is exposed to brute-force attacks

		SHOPS			
	acl	Id	City	Year	Sales
$t_1$	A	$t_1$	NY	2010	600
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		SHOPS <sup>e</sup>		
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# Exposure risk: Flattened and bucket/hash-based index

- **Flattened index:** an index value always represents the same plaintext value and users know the index function
  - ⇒ cells having the **same plaintext values** are exposed
  - ⇒ all **index-plaintext** value correspondences are exposed to brute-force attacks
  - ⇒ the **whole outsourced relation** is exposed to brute-force attacks
- **Bucket/hash-based index:** the same index value may represent different plaintext values
  - ⇒ users can only infer with certainty that certain values **do not correspond** to given cells

# Intuitive approach: ACL-based index

Index values directly depend on ACLs

		SHOPS			
acl		Id	City	Year	Sales
$t_1$	A	$t_1$ 001	NY	2010	600
$t_2$	A,B	$t_2$ 002	Rome	2010	700
$t_3$	B	$t_3$ 003	Rome	2011	600
$t_4$	A,C	$t_4$ 004	NY	2011	700
$t_5$	C	$t_5$ 005	Oslo	2011	700

		SHOPS <sup>e</sup>		
tid	tuple	$I_c$	$I_y$	$I_s$
1	$\alpha$	$I_A(\text{NY})$	$I_A(2010)$	$I_A(600)$
2	$\beta$	$I_{AB}(\text{Rome})$	$I_{AB}(2010)$	$I_{AB}(700)$
3	$\gamma$	$I_B(\text{Rome})$	$I_B(2011)$	$I_B(600)$
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+ block inference exposure

- considerable burden at the client side for query translation



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tid	tuple	I <sub>c</sub>	I <sub>y</sub>	I <sub>s</sub>
1	$\alpha$	$l_A(\text{NY})$	$l_A(2010)$	$l_A(600)$
2	$\beta$	$l_{AB}(\text{Rome})$	$l_{AB}(2010)$	$l_{AB}(700)$
3	$\gamma$	$l_B(\text{Rome})$	$l_B(2011)$	$l_B(600)$
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Ex: query submitted by user  $B$  with condition

Year=2010

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+ block inference exposure

- considerable burden at the client side for query translation

Ex: query submitted by user  $B$  with condition

$\text{Year}=2010 \implies I_y \text{ IN } \{l_B(2010), l_{AB}(2010), l_{BC}(2010), l_{ABC}(2010)\}$

# Intuitive approach: User-based index

- Each user  $u$  has an index function  $\iota_u$  that depends on a **private** piece of information shared with the data owner
- For each cell  $t[A]$  in  $r$  and user  $u$  in  $ac(t)$  there is index value  $\iota_u(t[A])$  in  $t^e[\mathbb{I}_A]$

# Intuitive approach: User-based index

- Each user  $u$  has an index function  $l_u$  that depends on a **private** piece of information shared with the data owner
- For each cell  $t[A]$  in  $r$  and user  $u$  in  $ac/(t)$  there is index value  $l_u(t[A])$  in  $t^e[I_A]$

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tid	tuple	$I_c$	$I_y$	$I_s$	
1	$\alpha$	$l_A(NY)$	$l_A(2010)$	$l_A(600)$	
2	$\beta$	$l_A(Rome)l_B(Rome)$	$l_A(2010)l_B(2010)$	$l_A(700)l_B(700)$	
3	$\gamma$	$l_B(Rome)$	$l_B(2011)$	$l_B(600)$	
4	$\delta$	$l_A(NY)l_C(NY)$	$l_A(2011)l_C(2011)$	$l_A(700)l_C(700)$	
5	$\epsilon$	$l_C(Oslo)$	$l_C(2011)$	$l_C(700)$	

# Intuitive approach: User-based index

- Each user  $u$  has an index function  $l_u$  that depends on a **private** piece of information shared with the data owner
- For each cell  $t[A]$  in  $r$  and user  $u$  in  $ac(t)$  there is index value  $l_u(t[A])$  in  $t^e[I_A]$

SHOPS						SHOPS <sup>e</sup>					
acl		Id	City	Year	Sales	tid	tuple	$I_c$	$I_y$	$I_s$	
$t_1$	A	$t_1$	001	NY	2010	600	1	$\alpha$	$l_A(\text{NY})$	$l_A(2010)$	$l_A(600)$
$t_2$	A,B	$t_2$	002	Rome	2010	700	2	$\beta$	$l_A(\text{Rome})l_B(\text{Rome})$	$l_A(2010)l_B(2010)$	$l_A(700)l_B(700)$
$t_3$	B	$t_3$	003	Rome	2011	600	3	$\gamma$	$l_B(\text{Rome})$	$l_B(2011)$	$l_B(600)$
$t_4$	A,C	$t_4$	004	NY	2011	700	4	$\delta$	$l_A(\text{NY})l_C(\text{NY})$	$l_A(2011)l_C(2011)$	$l_A(700)l_C(700)$
$t_5$	C	$t_5$	005	Oslo	2011	700	5	$\epsilon$	$l_C(\text{Oslo})$	$l_C(2011)$	$l_C(700)$

⇒ remains vulnerable to inference

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		SHOPS				
$acl$		Id	City	Year	Sales	
$t_1$	A	$t_1$				
$t_2$	A,B	$t_2$	002	Rome	2010	700
$t_3$	B	$t_3$	003	Rome	2011	600
$t_4$	A,C	$t_4$				
$t_5$	C	$t_5$				

		SHOPS <sup>e</sup>			
$tid$	$tuple$	$I_c$	$I_y$	$I_s$	
1	$\alpha$	$l_A(NY)$	$l_A(2010)$	$l_A(600)$	
2	$\beta$	$l_A(Rome)l_B(Rome)$	$l_A(2010)l_B(2010)$	$l_A(700)l_B(700)$	
3	$\gamma$	$l_B(Rome)$	$l_B(2011)$	$l_B(600)$	
4	$\delta$	$l_A(NY)l_C(NY)$	$l_A(2011)l_C(2011)$	$l_A(700)l_C(700)$	
5	$\epsilon$	$l_C(Oslo)$	$l_C(2011)$	$l_C(700)$	

⇒ remains vulnerable to inference

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		SHOPS				SHOPS <sup>e</sup>					
$acl$		Id	City	Year	Sales	tid	tuple	$I_c$	$I_y$	$I_s$	
$t_1$	A	$t_1$		2010		1	$\alpha$	$l_A(NY)$	$l_A(2010)$	$l_A(600)$	
$t_2$	A,B	$t_2$	002	Rome	2010	700	2	$\beta$	$l_A(Rome)l_B(Rome)$	$l_A(2010)l_B(2010)$	$l_A(700)l_B(700)$
$t_3$	B	$t_3$	003	Rome	2011	600	3	$\gamma$	$l_B(Rome)$	$l_B(2011)$	$l_B(600)$
$t_4$	A,C	$t_4$			700	4	$\delta$	$l_A(NY)l_C(NY)$	$l_A(2011)l_C(2011)$	$l_A(700)l_C(700)$	
$t_5$	C	$t_5$			700	5	$\epsilon$	$l_C(Oslo)$	$l_C(2011)$	$l_C(700)$	

⇒ remains vulnerable to inference

# Conflicting tuples

- Tuples  $t_i$  and  $t_j$  are in **conflict** over attribute  $A$ ,  $t_i \sim_A t_j$ , iff
  - have the **same value** for the attribute
  - can be accessed by **different but overlapping** sets of users



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		SHOPS			
	acl	Id	City	Year	Sales
$t_1$	A	001	NY	2010	600
$t_2$	A,B	002	Rome	2010	700
$t_3$	B	003	Rome	2011	600
$t_4$	A,C	004	NY	2011	700
$t_5$	C	005	Oslo	2011	700

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  - can be accessed by **different but overlapping** sets of users

		SHOPS				
	acl	Id	City	Year	Sales	
$t_1$	A	001	NY	2010	600	} $\sim_{City}$
$t_2$	A,B	002	Rome	2010	700	
$t_3$	B	003	Rome	2011	600	
$t_4$	A,C	004	NY	2011	700	
$t_5$	C	005	Oslo	2011	700	

$t_1 \sim_{City} t_4$

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  - have the **same value** for the attribute
  - can be accessed by **different but overlapping** sets of users

		SHOPS				
	acl	Id	City	Year	Sales	
$t_1$	A	001	NY	2010	600	} $\sim_{City}$
$t_2$	A,B	002	Rome	2010	700	
$t_3$	B	003	Rome	2011	600	
$t_4$	A,C	004	NY	2011	700	
$t_5$	C	005	Oslo	2011	700	

$t_1 \sim_{City} t_4$   
 $t_2 \sim_{City} t_3$

# Conflicting tuples

- Tuples  $t_i$  and  $t_j$  are in **conflict** over attribute  $A$ ,  $t_i \sim_A t_j$ , iff
  - have the **same value** for the attribute
  - can be accessed by **different but overlapping** sets of users

		SHOPS				
	acl	Id	City	Year	Sales	
$t_1$	A	001	NY	2010	600	} $\sim_{\text{Year}}$
$t_2$	A,B	002	Rome	2010	700	
$t_3$	B	003	Rome	2011	600	
$t_4$	A,C	004	NY	2011	700	
$t_5$	C	005	Oslo	2011	700	

$t_1 \sim_{\text{City}} t_4$   
 $t_2 \sim_{\text{City}} t_3$   
 $t_1 \sim_{\text{Year}} t_2$

# Conflicting tuples

- Tuples  $t_i$  and  $t_j$  are in **conflict** over attribute  $A$ ,  $t_i \sim_A t_j$ , iff
  - have the **same value** for the attribute
  - can be accessed by **different but overlapping** sets of users

		SHOPS				
	acl	Id	City	Year	Sales	
$t_1$	A	001	NY	2010	600	$t_1 \sim_{\text{City}} t_4$
$t_2$	A,B	002	Rome	2010	700	$t_2 \sim_{\text{City}} t_3$
$t_3$	B	003	Rome	2011	600	$t_1 \sim_{\text{Year}} t_2$
$t_4$	A,C	004	NY	2011	700	$t_4 \sim_{\text{Year}} t_5$
$t_5$	C	005	Oslo	2011	700	

# Conflicting tuples

- Tuples  $t_i$  and  $t_j$  are in **conflict** over attribute  $A$ ,  $t_i \sim_A t_j$ , iff
  - have the **same value** for the attribute
  - can be accessed by **different but overlapping** sets of users

		SHOPS				
	acl	Id	City	Year	Sales	
$t_1$	A	001	NY	2010	600	$t_1 \sim_{\text{City}} t_4$
$t_2$	A,B	002	Rome	2010	700	$t_2 \sim_{\text{City}} t_3$
$t_3$	B	003	Rome	2011	600	$t_1 \sim_{\text{Year}} t_2$
$t_4$	A,C	004	NY	2011	700	$t_4 \sim_{\text{Year}} t_5$
$t_5$	C	005	Oslo	2011	700	$t_2 \sim_{\text{Sales}} t_4$

# Conflicting tuples

- Tuples  $t_i$  and  $t_j$  are in **conflict** over attribute  $A$ ,  $t_i \sim_A t_j$ , iff
  - have the **same value** for the attribute
  - can be accessed by **different but overlapping** sets of users

		SHOPS				
	acl	Id	City	Year	Sales	
$t_1$	A	001	NY	2010	600	$t_1 \sim_{\text{City}} t_4$
$t_2$	A,B	002	Rome	2010	700	$t_2 \sim_{\text{City}} t_3$
$t_3$	B	003	Rome	2011	600	$t_1 \sim_{\text{Year}} t_2$
$t_4$	A,C	004	NY	2011	700	$t_4 \sim_{\text{Year}} t_5$
$t_5$	C	005	Oslo	2011	700	$t_2 \sim_{\text{Sales}} t_4$

$\sim_{\text{Sales}}$

$t_4 \sim_{\text{Sales}} t_5$

# Conflicting tuples

- Tuples  $t_i$  and  $t_j$  are in **conflict** over attribute  $A$ ,  $t_i \sim_A t_j$ , iff
  - have the **same value** for the attribute
  - can be accessed by **different but overlapping** sets of users

		SHOPS					
	acl	Id	City	Year	Sales		
$t_1$	A	001	NY	2010	600	} Sales	$t_1 \sim_{\text{City}} t_4$
$t_2$	A,B	002	Rome	2010	700		$t_2 \sim_{\text{City}} t_3$
$t_3$	B	003	Rome	2011	600		$t_1 \sim_{\text{Year}} t_2$
$t_4$	A,C	004	NY	2011	700		$t_4 \sim_{\text{Year}} t_5$
$t_5$	C	005	Oslo	2011	700		$t_2 \sim_{\text{Sales}} t_4$
							$t_4 \sim_{\text{Sales}} t_5$



# Tuple exposure

$t_i \sim_A \dots \sim_A t_j \implies t_i[A]$  is exposed to all users in  $acl(t_j) \setminus acl(t_i)$   
 $\implies t_j[A]$  is exposed to all users in  $acl(t_i) \setminus acl(t_j)$

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$t_i \sim_A \dots \sim_A t_j \implies t_i[A]$  is exposed to all users in  $acl(t_j) \setminus acl(t_i)$   
 $\implies t_j[A]$  is exposed to all users in  $acl(t_i) \setminus acl(t_j)$

SHOPS					SHOPS <sup>e</sup>					
acl		Id	City	Year	Sales	tid	tuple	I <sub>c</sub>	I <sub>y</sub>	I <sub>s</sub>
t <sub>1</sub> A	t <sub>1</sub>					1	α	I <sub>A</sub> (NY)	I <sub>A</sub> (2010)	I <sub>A</sub> (600)
t <sub>2</sub> A,B	t <sub>2</sub>	002	Rome	2010	700	2	β	I <sub>A</sub> (Rome)I <sub>B</sub> (Rome)	I <sub>A</sub> (2010)I <sub>B</sub> (2010)	I <sub>A</sub> (700)I <sub>B</sub> (700)
t <sub>3</sub> B	t <sub>3</sub>	003	Rome	2011	600	3	γ	I <sub>B</sub> (Rome)	I <sub>B</sub> (2011)	I <sub>B</sub> (600)
t <sub>4</sub> A,C	t <sub>4</sub>					4	δ	I <sub>A</sub> (NY)I <sub>C</sub> (NY)	I <sub>A</sub> (2011)I <sub>C</sub> (2011)	I <sub>A</sub> (700)I <sub>C</sub> (700)
t <sub>5</sub> C	t <sub>5</sub>					5	ε	I <sub>C</sub> (Oslo)	I <sub>C</sub> (2011)	I <sub>C</sub> (700)

# Tuple exposure

$t_i \sim_A \dots \sim_A t_j \implies t_i[A]$  is exposed to all users in  $acl(t_j) \setminus acl(t_i)$   
 $\implies t_j[A]$  is exposed to all users in  $acl(t_i) \setminus acl(t_j)$

SHOPS					SHOPS <sup>e</sup>						
acl		Id	City	Year	Sales	tid	tuple	I <sub>c</sub>	I <sub>y</sub>	I <sub>s</sub>	
$t_1$	A	$t_1$		2010		1	$\alpha$	$l_A(NY)$	$l_A(2010)$	$l_A(600)$	
$t_2$	A,B	$t_2$	002	Rome	2010	700	2	$\beta$	$l_A(Rome)l_B(Rome)$	$l_A(2010)l_B(2010)$	$l_A(700)l_B(700)$
$t_3$	B	$t_3$	003	Rome	2011	600	3	$\gamma$	$l_B(Rome)$	$l_B(2011)$	$l_B(600)$
$t_4$	A,C	$t_4$					4	$\delta$	$l_A(NY)l_C(NY)$	$l_A(2011)l_C(2011)$	$l_A(700)l_C(700)$
$t_5$	C	$t_5$					5	$\epsilon$	$l_C(Oslo)$	$l_C(2011)$	$l_C(700)$

- $t_1 \sim_{\text{Year}} t_2 \implies t_1[\text{Year}]$  is exposed to B

# Tuple exposure

$t_i \sim_A \dots \sim_A t_j \implies t_i[A]$  is exposed to all users in  $acl(t_j) \setminus acl(t_i)$   
 $\implies t_j[A]$  is exposed to all users in  $acl(t_i) \setminus acl(t_j)$

SHOPS					SHOPS <sup>e</sup>						
acl		Id	City	Year	Sales	tid	tuple	I <sub>c</sub>	I <sub>y</sub>	I <sub>s</sub>	
$t_1$	A	$t_1$		2010		1	$\alpha$	$I_A(\text{NY})$	$I_A(2010)$	$I_A(600)$	
$t_2$	A,B	$t_2$	002	Rome	2010	700	2	$\beta$	$I_A(\text{Rome})I_B(\text{Rome})$	$I_A(2010)I_B(2010)$	$I_A(700)I_B(700)$
$t_3$	B	$t_3$	003	Rome	2011	600	3	$\gamma$	$I_B(\text{Rome})$	$I_B(2011)$	$I_B(600)$
$t_4$	A,C	$t_4$			700	4	$\delta$	$I_A(\text{NY})I_C(\text{NY})$	$I_A(2011)I_C(2011)$	$I_A(700)I_C(700)$	
$t_5$	C	$t_5$				5	$\epsilon$	$I_C(\text{Oslo})$	$I_C(2011)$	$I_C(700)$	

- $t_1 \sim_{\text{Year}} t_2 \implies t_1[\text{Year}]$  is exposed to  $B$
- $t_2 \sim_{\text{Sales}} t_4 \implies t_4[\text{Sales}]$  is exposed to  $B$

# Tuple exposure

$t_i \sim_A \dots \sim_A t_j \implies t_i[A]$  is exposed to all users in  $acl(t_j) \setminus acl(t_i)$   
 $\implies t_j[A]$  is exposed to all users in  $acl(t_i) \setminus acl(t_j)$

SHOPS					SHOPS <sup>e</sup>						
acl		Id	City	Year	Sales	tid	tuple	I <sub>c</sub>	I <sub>y</sub>	I <sub>s</sub>	
$t_1$	A	$t_1$			2010	1	$\alpha$	$I_A(\text{NY})$	$I_A(2010)$	$I_A(600)$	
$t_2$	A,B	$t_2$	002	Rome	2010	700	2	$\beta$	$I_A(\text{Rome})I_B(\text{Rome})$	$I_A(2010)I_B(2010)$	$I_A(700)I_B(700)$
$t_3$	B	$t_3$	003	Rome	2011	600	3	$\gamma$	$I_B(\text{Rome})$	$I_B(2011)$	$I_B(600)$
$t_4$	A,C	$t_4$				700	4	$\delta$	$I_A(\text{NY})I_C(\text{NY})$	$I_A(2011)I_C(2011)$	$I_A(700)I_C(700)$
$t_5$	C	$t_5$				700	5	$\epsilon$	$I_C(\text{Oslo})$	$I_C(2011)$	$I_C(700)$

- $t_1 \sim_{\text{Year}} t_2 \implies t_1[\text{Year}]$  is exposed to  $B$
- $t_2 \sim_{\text{Sales}} t_4 \implies t_4[\text{Sales}]$  is exposed to  $B$
- $t_2 \sim_{\text{Sales}} t_4 \sim_{\text{Sales}} t_5 \implies t_5[\text{Sales}]$  is exposed to  $B$

# Safe index

- An index function is **safe** if conflicting tuples have **different index values** for all the users who can access them
- The index values computed by a safe index function **cannot be exploited** for inference purposes
- We define a safe index for attribute  $A$  by
  - **safely partitioning** tuples in clusters such that tuples in conflict over  $A$  do not belong to the same cluster
  - adopting a **different salt** for each cluster in the definition of the index function for  $A$
- To minimize the burden at the client side for query translation, **the number of salts** (i.e., the number of clusters) must be **minimized**

# Conflict graph

- Our minimization problem is equivalent to the **minimum vertex coloring problem**
- A **conflict graph**  $G_A(V_A, E_A)$  is a non-directed graph with

	<b>acl</b>
$t_1$	A
$t_2$	A,B
$t_3$	B
$t_4$	A,C
$t_5$	C

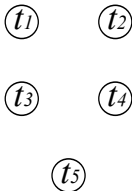
	<b>Id</b>	<b>City</b>	<b>Year</b>	<b>Sales</b>
$t_1$	001	NY	2010	600
$t_2$	002	Rome	2010	700
$t_3$	003	Rome	2011	600
$t_4$	004	NY	2011	700
$t_5$	005	Oslo	2011	700

# Conflict graph

- Our minimization problem is equivalent to the **minimum vertex coloring problem**
- A **conflict graph**  $G_A(V_A, E_A)$  is a non-directed graph with
  - a vertex in  $V_A$  for each tuple in  $r$

		SHOPS			
	<b>acl</b>	<b>Id</b>	<b>City</b>	<b>Year</b>	<b>Sales</b>
$t_1$	A	001	NY	2010	600
$t_2$	A,B	002	Rome	2010	700
$t_3$	B	003	Rome	2011	600
$t_4$	A,C	004	NY	2011	700
$t_5$	C	005	Oslo	2011	700

$G_{city}$



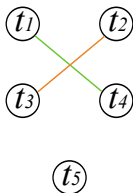


# Conflict graph

- Our minimization problem is equivalent to the **minimum vertex coloring problem**
- A **conflict graph**  $G_A(V_A, E_A)$  is a non-directed graph with
  - a vertex in  $V_A$  for each tuple in  $r$
  - an edge  $(t_i, t_j)$  in  $E_A$  iff  $t_i \sim_A t_j$

SHOPS					
	acl	Id	City	Year	Sales
$t_1$	A	001	NY	2010	600
$t_2$	A,B	002	Rome	2010	700
$t_3$	B	003	Rome	2011	600
$t_4$	A,C	004	NY	2011	700
$t_5$	C	005	Oslo	2011	700

$G_{\text{city}}$

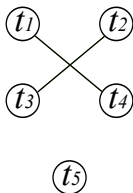


# Conflict graph

- Our minimization problem is equivalent to the **minimum vertex coloring problem**
- A **conflict graph**  $G_A(V_A, E_A)$  is a non-directed graph with
  - a vertex in  $V_A$  for each tuple in  $r$
  - an edge  $(t_i, t_j)$  in  $E_A$  iff  $t_i \sim_A t_j$
- A **minimum coloring** of  $G_A$  is a **minimum safe partitioning** of  $r$  that solves conflicts w.r.t.  $A$

		SHOPS			
	acl	Id	City	Year	Sales
$t_1$	A	001	NY	2010	600
$t_2$	A,B	002	Rome	2010	700
$t_3$	B	003	Rome	2011	600
$t_4$	A,C	004	NY	2011	700
$t_5$	C	005	Oslo	2011	700

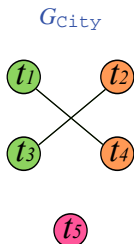
$G_{\text{city}}$



# Conflict graph

- Our minimization problem is equivalent to the **minimum vertex coloring problem**
- A **conflict graph**  $G_A(V_A, E_A)$  is a non-directed graph with
  - a vertex in  $V_A$  for each tuple in  $r$
  - an edge  $(t_i, t_j)$  in  $E_A$  iff  $t_i \sim_A t_j$
- A **minimum coloring** of  $G_A$  is a **minimum safe partitioning** of  $r$  that solves conflicts w.r.t.  $A$

		SHOPS			
	acl	Id	City	Year	Sales
$t_1$	A	001	NY	2010	600
$t_2$	A,B	002	Rome	2010	700
$t_3$	B	003	Rome	2011	600
$t_4$	A,C	004	NY	2011	700
$t_5$	C	005	Oslo	2011	700

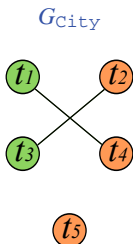


Safe but **not minimum** coloring

# Conflict graph

- Our minimization problem is equivalent to the **minimum vertex coloring problem**
- A **conflict graph**  $G_A(V_A, E_A)$  is a non-directed graph with
  - a vertex in  $V_A$  for each tuple in  $r$
  - an edge  $(t_i, t_j)$  in  $E_A$  iff  $t_i \sim_A t_j$
- A **minimum coloring** of  $G_A$  is a **minimum safe partitioning** of  $r$  that solves conflicts w.r.t.  $A$

		SHOPS			
	acl	Id	City	Year	Sales
$t_1$	A	001	NY	2010	600
$t_2$	A,B	002	Rome	2010	700
$t_3$	B	003	Rome	2011	600
$t_4$	A,C	004	NY	2011	700
$t_5$	C	005	Oslo	2011	700



Safe and minimum coloring

# Computing a safe index

Index function  $\iota_u$  for user  $u$  over attribute  $A$  is defined applying **randomly generated salts** to tuples

- tuples in different clusters are assigned different salts
- tuples in the same cluster are assigned the same salt

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		SHOPS				
	acl	Id	City	Year	Sales	
$t_1$	A	$t_1$	001	NY	2010	600
$t_2$	A,B	$t_2$	002	Rome	2010	700
$t_3$	B	$t_3$	003	Rome	2011	600
$t_4$	A,C	$t_4$	004	NY	2011	700
$t_5$	C	$t_5$	005	Oslo	2011	700

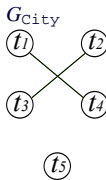
		SHOPS <sup>e</sup>		
tid	tuple	$I_c$	$I_y$	$I_s$
1	$\alpha$			
2	$\beta$			
3	$\gamma$			
4	$\delta$			
5	$\varepsilon$			

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$t_2$	A,B	002	Rome	2010	700
$t_3$	B	003	Rome	2011	600
$t_4$	A,C	004	NY	2011	700
$t_5$	C	005	Oslo	2011	700



SHOPS<sup>e</sup>

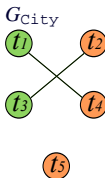
tid	tuple	$I_c$	$I_y$	$I_s$
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SHOPS<sup>e</sup>

tid	tuple	$I_c$	$I_y$	$I_s$
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3	$\gamma$			
4	$\delta$			
5	$\epsilon$			

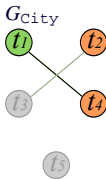


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$t_3$	B	003	Rome	2011	600
$t_4$	A,C	004	NY	2011	700
$t_5$	C	005	Oslo	2011	700



SHOPS<sup>e</sup>

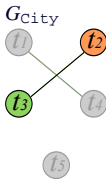
tid	tuple	$I_c$	$I_y$	$I_s$
1	$\alpha$	$t_A(\text{NY}, s_A)$		
2	$\beta$	$t_A(\text{Rome}, s'_A)$		
3	$\gamma$			
4	$\delta$	$t_A(\text{NY}, s'_A)$		
5	$\epsilon$			

# Computing a safe index

Index function  $l_u$  for user  $u$  over attribute  $A$  is defined applying randomly generated salts to tuples

- tuples in different clusters are assigned different salts
- tuples in the same cluster are assigned the same salt

acl		SHOPS			
		Id	City	Year	Sales
$t_1$	A	$t_1$ 001	NY	2010	600
$t_2$	A,B	$t_2$ 002	Rome	2010	700
$t_3$	B	$t_3$ 003	Rome	2011	600
$t_4$	A,C	$t_4$ 004	NY	2011	700
$t_5$	C	$t_5$ 005	Oslo	2011	700



SHOPS<sup>e</sup>

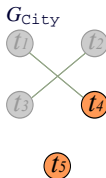
tid	tuple	$I_c$	$I_y$	$I_s$
1	$\alpha$	$l_A(\text{NY}, s_A)$		
2	$\beta$	$l_A(\text{Rome}, s'_A)$ $l_B(\text{Rome}, s_B)$		
3	$\gamma$	$l_B(\text{Rome}, s'_B)$		
4	$\delta$	$l_A(\text{NY}, s'_A)$		
5	$\epsilon$			

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$t_3$	B	003	Rome	2011	600
$t_4$	A,C	004	NY	2011	700
$t_5$	C	005	Oslo	2011	700



SHOPS<sup>e</sup>

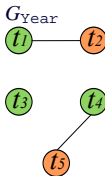
tid	tuple	$I_c$	$I_y$	$I_s$
1	$\alpha$	$\iota_A(\text{NY}, s_A)$		
2	$\beta$	$\iota_A(\text{Rome}, s'_A) \iota_B(\text{Rome}, s_B)$		
3	$\gamma$	$\iota_B(\text{Rome}, s'_B)$		
4	$\delta$	$\iota_A(\text{NY}, s'_A) \iota_C(\text{NY}, s_C)$		
5	$\epsilon$	$\iota_C(\text{Oslo}, s_C)$		

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SHOPS<sup>e</sup>

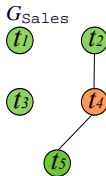
tid	tuple	$I_c$	$I_y$	$I_s$
1	$\alpha$	$t_A(\text{NY}, s_A)$	$t_A(2010, s_A)$	
2	$\beta$	$t_A(\text{Rome}, s'_A) t_B(\text{Rome}, s_B)$	$t_A(2010, s'_A) t_B(2010, s_B)$	
3	$\gamma$	$t_B(\text{Rome}, s'_B)$	$t_B(2011, s'_B)$	
4	$\delta$	$t_A(\text{NY}, s'_A) t_C(\text{NY}, s_C)$	$t_A(2011, s_A) t_C(2011, s_C)$	
5	$\epsilon$	$t_C(\text{Oslo}, s_C)$	$t_C(2011, s'_C)$	

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$t_3$	B	$t_3$ 003	Rome	2011	600
$t_4$	A,C	$t_4$ 004	NY	2011	700
$t_5$	C	$t_5$ 005	Oslo	2011	700



SHOPS<sup>e</sup>

tid	tuple	$I_c$	$I_y$	$I_s$
1	$\alpha$	$I_A(NY, s_A)$	$I_A(2010, s_A)$	$I_A(600, s_A)$
2	$\beta$	$I_A(Rome, s'_A) I_B(Rome, s_B)$	$I_A(2010, s'_A) I_B(2010, s_B)$	$I_A(700, s_A) I_B(700, s_B)$
3	$\gamma$	$I_B(Rome, s'_B)$	$I_B(2011, s'_B)$	$I_B(600, s_B)$
4	$\delta$	$I_A(NY, s'_A) I_C(NY, s_C)$	$I_A(2011, s_A) I_C(2011, s_C)$	$I_A(700, s'_A) I_C(700, s_C)$
5	$\epsilon$	$I_C(Oslo, s_C)$	$I_C(2011, s'_C)$	$I_C(700, s'_C)$

# Relation level approach (1)

- The conflict graph can also be defined over the **whole schema** of the outsourced relation, defining a unique partitioning of  $r$
- Each tuple  $t$  is associated with a **unique salt**, used to compute all the index values associated with  $t$
- Conflict graph  $G_R(V_R, E_R)$  is a non-directed graph with

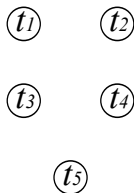
		SHOPS			
	acl	Id	City	Year	Sales
$t_1$	A	001	NY	2010	600
$t_2$	A,B	002	Rome	2010	700
$t_3$	B	003	Rome	2011	600
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		SHOPS			
	acl	Id	City	Year	Sales
$t_1$	A	001	NY	2010	600
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$G_{SHOPS}$

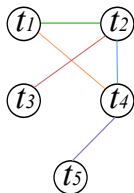


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- Conflict graph  $G_R(V_R, E_R)$  is a non-directed graph with
  - a vertex in  $V_R$  for each tuple in  $r$
  - an edge  $(t_i, t_j)$  in  $E_R$  if  $\exists A \in R$  s.t.  $t_i \sim_A t_j$

	acl	SHOPS			
		Id	City	Year	Sales
$t_1$	A	001	NY	2010	600
$t_2$	A,B	002	Rome	2010	700
$t_3$	B	003	Rome	2011	600
$t_4$	A,C	004	NY	2011	700
$t_5$	C	005	Oslo	2011	700

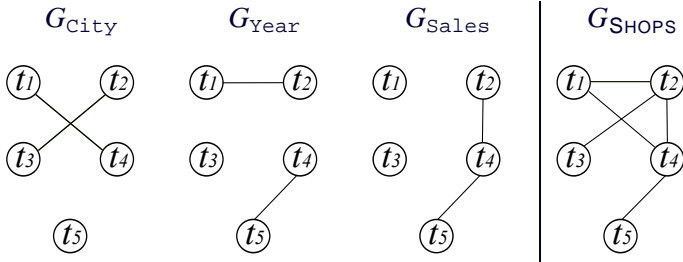
$G_{SHOPS}$





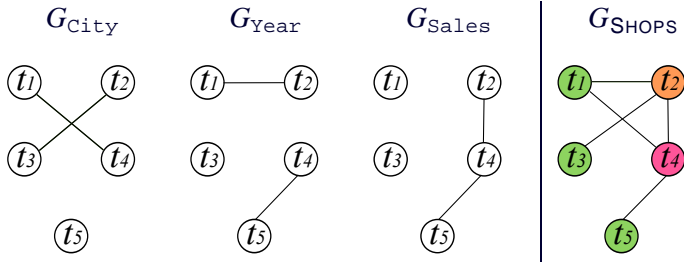
## Relation level approach (2)

- Conflict graph  $G_R(V_R, E_R)$  can be obtained by **composing** the conflict graphs  $G_A(V_A, E_A)$  of attributes in  $R$ 
  - a coloring for  $G_R$  is a coloring for  $G_A$ , with  $A \in R$ , but not viceversa
  - a minimum coloring for  $G_R$  may not be minimum for  $G_A$ , with  $A \in R$



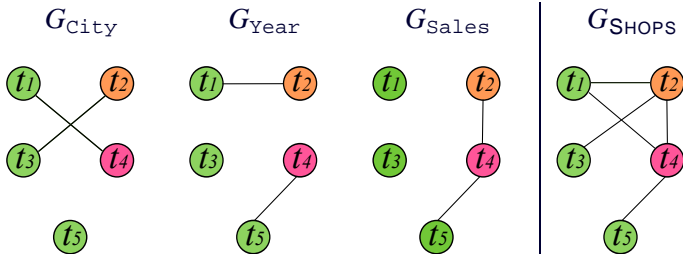
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## Relation level approach (2)

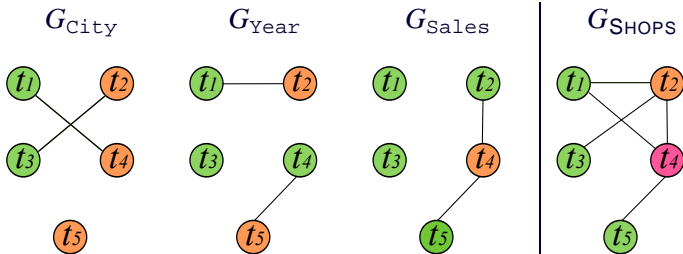
- Conflict graph  $G_R(V_R, E_R)$  can be obtained by **composing** the conflict graphs  $G_A(V_A, E_A)$  of attributes in  $R$ 
  - a coloring for  $G_R$  is a coloring for  $G_A$ , with  $A \in R$ , but not viceversa
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Safe but **not minimum** coloring

## Relation level approach (2)

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Safe and **minimum** coloring

# Query evaluation

- Each user  $u$  knows
  - index function  $l_u$
  - the maximum number of salts  $n_{A,u}$  used to define the index for attribute  $A$
  - the pseudo-random function used to generate salts
- Condition  $A=v$  in a query submitted by user  $u$  is translated as  $I_A \text{ IN } V$ , with
  - $I_A$ : index over  $A$
  - $V=\{l_u(v, s_1), \dots, l_u(v, s_{n_{A,u}})\}$ : values obtained applying  $l_u$  to  $v$  combined with each of the  $n_{A,u}$  salts

# Query evaluation: Example

SHOPS						
acl		Id	City	Year	Sales	
$t_1$	A	$t_1$	001	NY	2010	600
$t_2$	A,B	$t_2$	002	Rome	2010	700
$t_3$	B	$t_3$	003	Rome	2011	600
$t_4$	A,C	$t_4$	004	NY	2011	700
$t_5$	C	$t_5$	005	Oslo	2011	700

SHOPS <sup>e</sup>				
tid	tuple	$I_c$	$I_y$	$I_s$
1	$\alpha$	$I_A(NY, s_A)$	$I_A(2010, s_A)$	$I_A(600, s_A)$
2	$\beta$	$I_A(Rome, s'_A) I_B(Rome, s_B)$	$I_A(2010, s'_A) I_B(2010, s_B)$	$I_A(700, s_A) I_B(700, s_B)$
3	$\gamma$	$I_B(Rome, s'_B)$	$I_B(2011, s'_B)$	$I_B(600, s_B)$
4	$\delta$	$I_A(NY, s'_A) I_C(NY, s_C)$	$I_A(2011, s'_A) I_C(2011, s_C)$	$I_A(700, s'_A) I_C(700, s_C)$
5	$\epsilon$	$I_C(Oslo, s'_C)$	$I_C(2011, s'_C)$	$I_C(700, s'_C)$

# Query evaluation: Example

		SHOPS			
	acl	Id	City	Year	Sales
$t_1$	A				
$t_2$	A,B	002	Rome	2010	700
$t_3$	B	003	Rome	2011	600
$t_4$	A,C				
$t_5$	C				

		SHOPS <sup>e</sup>		
tid	tuple	$I_c$	$I_y$	$I_s$
1	$\alpha$	$I_A(NY, s_A)$	$I_A(2010, s_A)$	$I_A(600, s_A)$
2	$\beta$	$I_A(Rome, s'_A) I_B(Rome, s_B)$	$I_A(2010, s'_A) I_B(2010, s_B)$	$I_A(700, s_A) I_B(700, s_B)$
3	$\gamma$	$I_B(Rome, s'_B)$	$I_B(2011, s'_B)$	$I_B(600, s_B)$
4	$\delta$	$I_A(NY, s'_A) I_C(NY, s_C)$	$I_A(2011, s'_A) I_C(2011, s_C)$	$I_A(700, s'_A) I_C(700, s_C)$
5	$\epsilon$	$I_C(Oslo, s_C)$	$I_C(2011, s'_C)$	$I_C(700, s'_C)$

Query by  $B$ , who has 2 salts for Year

```
SELECT City, Sales
FROM SHOPS
WHERE Year=2010
```



# Query evaluation: Example

		SHOPS			
	acl	Id	City	Year	Sales
$t_1$	A				
$t_2$	A,B	002	Rome	2010	700
$t_3$	B	003	Rome	2011	600
$t_4$	A,C				
$t_5$	C				

		SHOPS <sup>e</sup>		
tid	tuple	$I_c$	$I_y$	$I_s$
1	$\alpha$	$I_A(NY, s_A)$	$I_A(2010, s_A)$	$I_A(600, s_A)$
2	$\beta$	$I_A(\mathbf{Rome}, s'_A) I_B(\mathbf{Rome}, s_B)$	$I_A(\mathbf{2010}, s'_A) I_B(\mathbf{2010}, s_B)$	$I_A(\mathbf{700}, s_A) I_B(\mathbf{700}, s_B)$
3	$\gamma$	$I_B(\mathbf{Rome}, s'_B)$	$I_B(2011, s'_B)$	$I_B(600, s_B)$
4	$\delta$	$I_A(NY, s'_A) I_C(NY, s_C)$	$I_A(2011, s_A) I_C(2011, s_C)$	$I_A(700, s'_A) I_C(700, s_C)$
5	$\epsilon$	$I_C(\mathbf{Oslo}, s'_C)$	$I_C(2011, s'_C)$	$I_C(700, s'_C)$

Query by  $B$ , who has 2 salts for Year translates to

```
SELECT City, Sales
FROM SHOPS
WHERE Year=2010
```

⇒

```
SELECT tuple
FROM SHOPSe
WHERE  $I_y$  IN  $\{I_B(2010, s_B), I_B(2010, s'_B)\}$ 
```

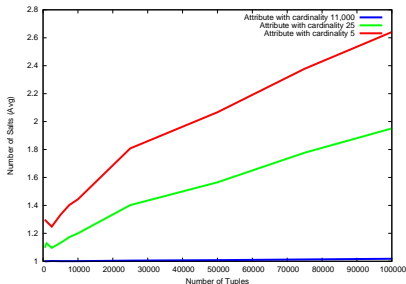


# Experimental results (1)

- **Relational table** built starting from the **TPC-H** benchmark
  - three attributes with 5, 25, and 11,000 distinct values
  - from 500 to 100,000 tuples
- **Access control policy** obtained extracting the authorship information from the **DBLP** repository
  - each paper is represented by a tuple in the table
  - each author can access all and only her papers
- **Attribute level** and **relation level** approaches compared w.r.t.
  - the **number of clusters** composing a safe partitioning (i.e., upper bound of the number of salts required)
  - the average **number of salts per user** (i.e., user overhead in query translation)

# Experimental results (2)

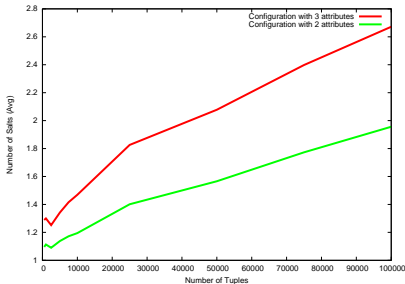
## Attribute level



- Attribute level salt, three attributes:

- cardinality 5
- cardinality 25
- cardinality 11000

## Relation level



- Relation level salt, two relations:

- three attributes, with cardinality 5, 25, 11000
- two attributes, with cardinality 25, 11000

## Experimental results (3)

Specifying salts at the attribute level (in contrast to relation)

- + permits to reduce the overhead of queries with condition on the most selective attributes (the difference for non-selective attributes is minimal)
  - requires storing a different value for the number of salts for every attribute (in contrast to a value for the whole relation), for every user
- ⇒ If queries over selective attributes are more frequent: the attribute level approach is preferred; otherwise, the relation level approach is preferred for its simplicity and limited storage overhead

# Conclusions

- We have proposed an **index** for accessing encrypted data that are made accessible **selectively**
  - it is **safe** from inference
  - it enjoys **limited overhead** in query evaluation
  - the approach is also applicable to indexing techniques other than direct index
- Future works
  - protection against the server observing **multiple queries**
  - protection against **collusion** between users and server