

# When the Signal is in the Noise: Exploiting Diffix's Sticky Noise

**Andrea Gadotti\***, Florimond Houssiau\*, **Luc Rocher\***,  
Benjamin Livshits, Yves-Alexandre de Montjoye

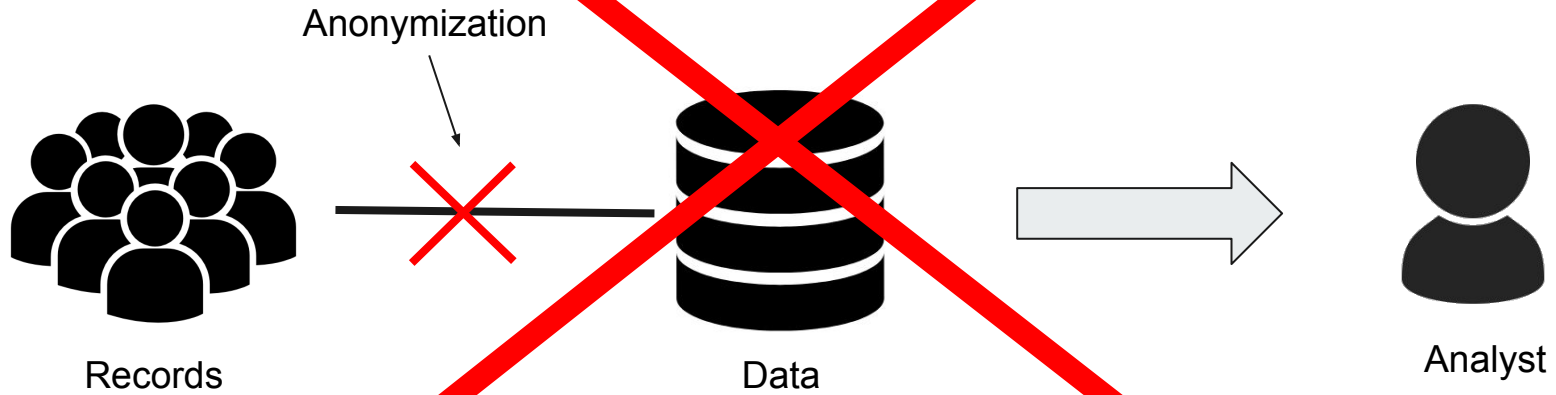
Imperial College  
London



 UCLouvain

**fnrs**  
LA LIBERTÉ DE CHERCHER

# Anonymization



# A different model: data query systems

## From de-identification...

- Individual-level data
- No control over analyses



Data

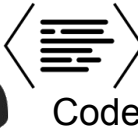


Analyst

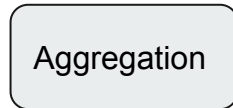
## ... to data query systems

- Aggregation
- Additional security and privacy measures

WHAT IF ANALYST IS MALICIOUS?



Code



~~"How many people  
named Bob have a  
salary  $\leq$  £2000"~~

Q1 = "How many people have a salary  $\leq$  £2000"

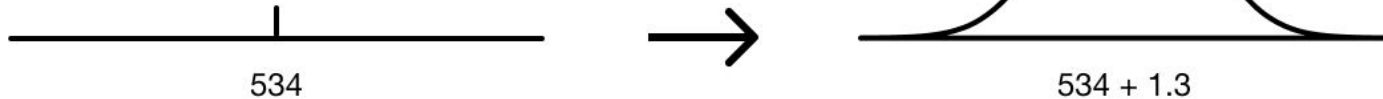
Q2 = "How many people not named Bob have a salary  $\leq$  £2000"

$$\rightarrow Q1 - Q2 = [0 \text{ or } 1]$$

This is called *differencing attack*.

# Random noise to prevent privacy attacks

*“How many people have a salary  $\leq$  £1500?”*



# Reconstruction attacks and differential privacy

First **reconstruction attack** (Dinur and Nissim, 2003).

If noise is not enough → attacker can reconstruct the full dataset in polynomial time.

Since then, the attack has been generalized and improved.

One solution: **differential privacy** (Dwork et al., 2006).

Pros:

- provable and meaningful guarantee
- mathematical framework for privacy/utility

Cons (as of today):

- adds too much noise in many cases
- hard to allow many queries
- hard to provide good usability/flexibility

---

A heuristic-based data query  
system: Diffix



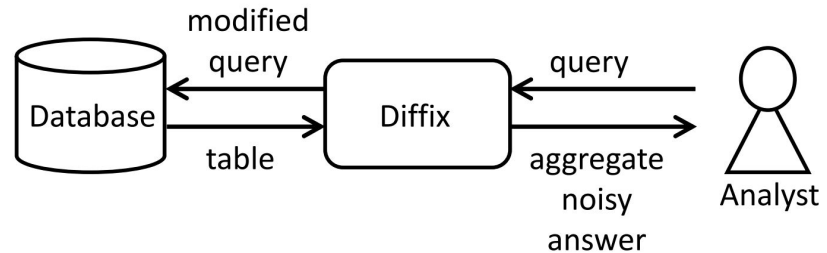
# Diffix is a privacy-preserving database system

Diffix is a patented commercial system developed by the company *Aircloak* and researchers at the Max Planck Institute for Software Systems.



Diffix operates as an **SQL proxy** between the analyst and the database.

- **Rich SQL syntax**
- **Little noise**
- **Infinite queries**



# Diffix's noise mechanism: sticky noise

An analyst submits a (count) SQL query Q to Diffix:

```
SELECT count(*)  
FROM table  
WHERE condition1 AND condition2 [AND ... ]
```

To which Diffix responds with:

output = true count + **static noise** + **dynamic noise**

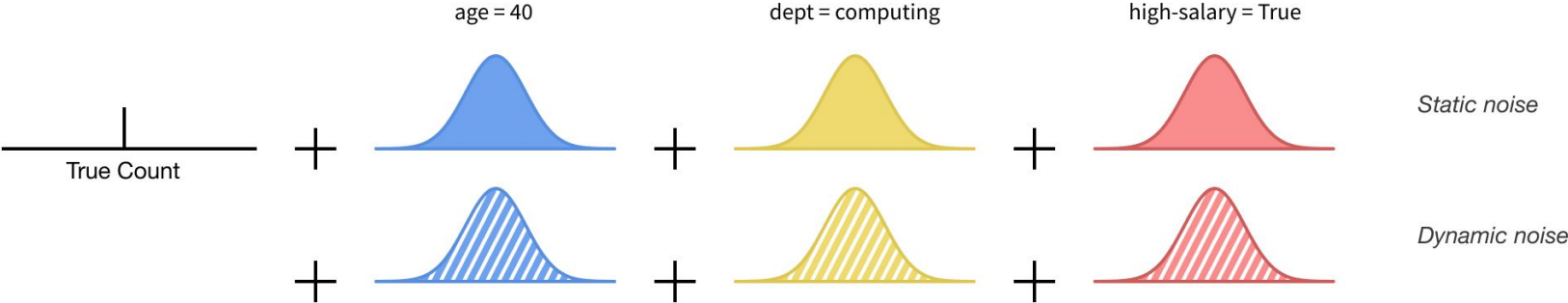
**static noise** ← query syntax of Q

**dynamic noise** ← query syntax and **user set** of Q

Both noises are **sticky**: issuing the same query gives the same noise

# Diffix's noise mechanism: sticky noise

$Q = \text{count}(\text{age} = 40 \wedge \text{dept} = \text{Computing} \wedge \text{high-salary} = \text{True})$



Each noise  $\sim N(0,1)$

More measures...

---

Our noise-exploitation attack(s) on Diffix:  
Exploiting data-dependent noise

# Attack model and assumptions

- Dataset has  $d$  attributes

$$\{a_1, \dots, a_{d-1}, s\}$$

- One target at a time: Bob
- Attacker wants to infer Bob's attribute  $s$  (binary).
- Attacker knows:
  - Bob's record is in the dataset
  - The value of  $k$  attributes about Bob

**Example** (with  $d=3, k=2$ )

Dataset attributes:

`{age, department, high-salary}`

Secret attribute: `high-salary`

Bob's record: `(40, Computing, true)`

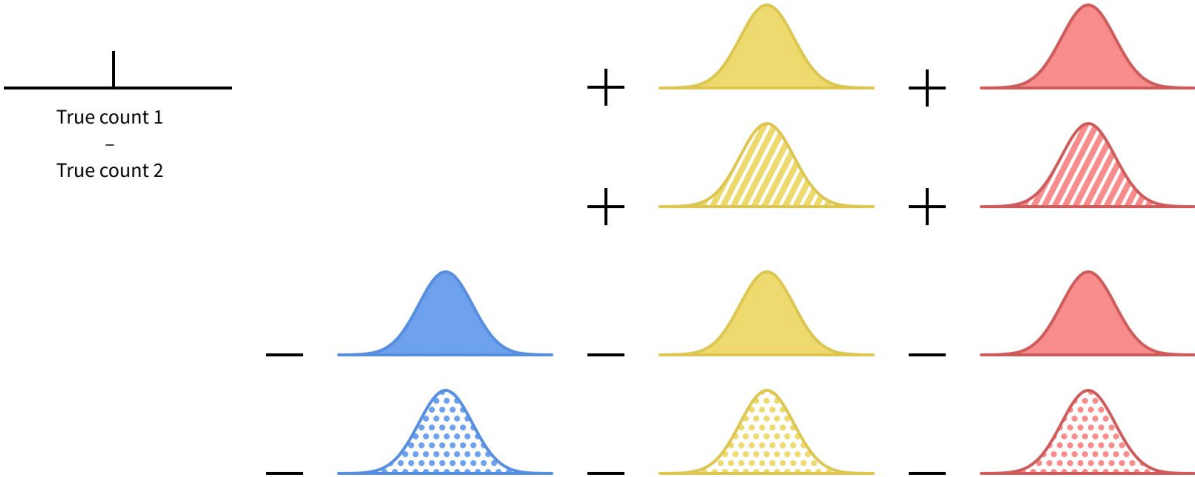
Attacker knows: `(40, Computing)`

# Differential attack

Q1 = count( dept = Computing  $\wedge$  high-salary = True )  
 Q2 = count( age  $\neq$  40  $\wedge$  dept = Computing  $\wedge$  high-salary = True )

**Bob:**  
 age = 40  
 dept = computing  
 high-salary = ?  
 (unique)

Output of Q1 - Q2

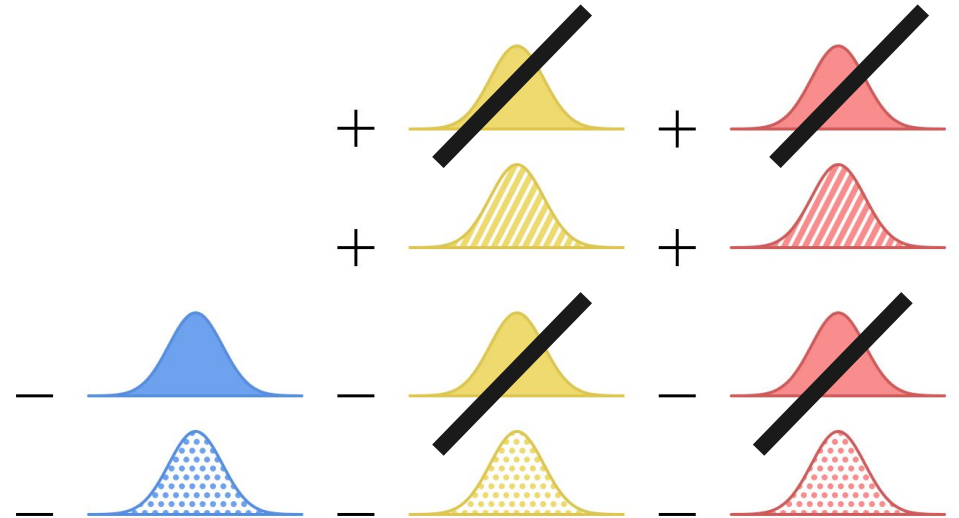


# Differential attack

Q1 = count( dept = Computing  $\wedge$  high-salary = True )  
Q2 = count( age  $\neq$  40  $\wedge$  dept = Computing  $\wedge$  high-salary = True )

**Bob:**  
age = 40  
dept = computing  
high-salary = ?  
(unique)

Output of Q1 - Q2  
if high-salary = True



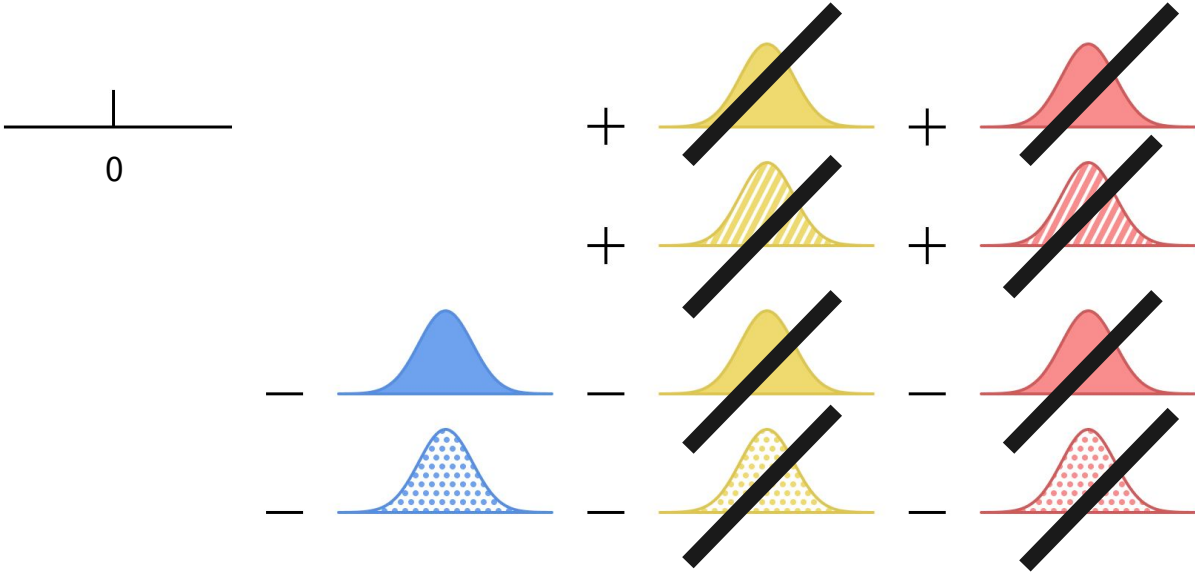
# Differential attack

```

Q1 = count(      dept = Computing ^ high-salary = True )
Q2 = count( age ≠ 40 ^ dept = Computing ^ high-salary = True )
    
```

**Bob:**  
 age = 40  
 dept = computing  
 high-salary = ?  
 (unique)

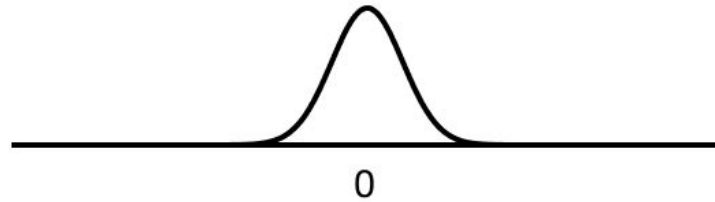
Output of Q1 - Q2  
 if high-salary = False





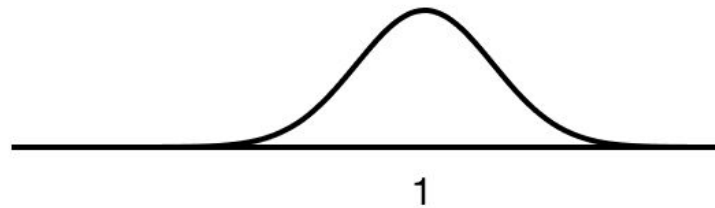
# Differential attack

if `high-salary = True`



$$Q1 - Q2 \sim N(\mu=0, \sigma=2)$$

if `high-salary = False`

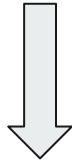


$$Q1 - Q2 \sim N(\mu=1, \sigma=2k+2)$$

# The cloning attack

Main issues with the differential attack:

1. Assumes that Bob is **unique**
2. Attack queries likely to be **suppressed**



Accuracy not great in some cases

Improved attack: **cloning attack**

- Much better accuracy
- Relies on weaker notion of uniqueness

# Value-uniqueness

**Definition:** A record is value-unique w.r.t. a set of attributes  $\{a_1, \dots, a_k\}$  if all records sharing the same attributes also have the same secret attribute.

**Note:**  
Value-uniqueness is detected automatically by the cloning attack

## Example

Bob's record  
(value-unique)

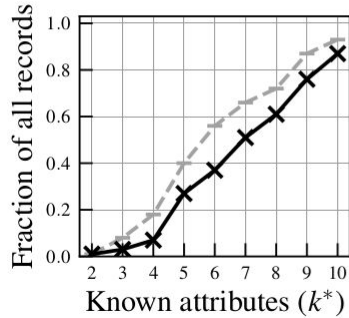
Alice's record  
(not value-unique)

age	dept	high-salary
40	computing	true
40	computing	true
34	math	false
34	math	true

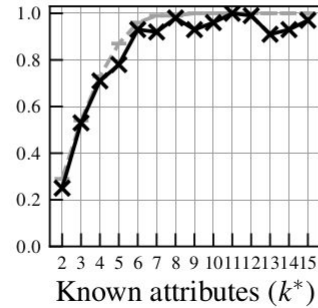
# Results for the cloning attack

--- Value-unique    —× Correctly inferred

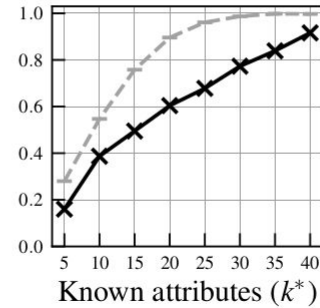
## ADULT



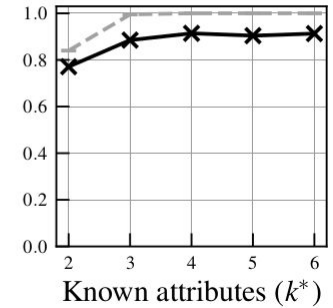
## CREDIT



## CENSUS



## CDR



- Attacked and correctly inferred: **~90% of all users**
- Modified attack: **32 queries/user**

# Aircloak's proposed patch

## **Aircloak's patch**

Remove “dangerous” (low effect) conditions from queries (depending on data).

*Comment.* Does not address core vulnerability and potentially introduces new one.

**Expected patch date:** *Q4 2019*

# Other attacks on Diffix

## Membership inference attack

by A. Pyrgelis, C. Troncoso, E. De Cristofaro

**idea:** infer whether an individual is in the dataset by training a classifier to tell this from aggregate data.

**based on:** Apostolos Pyrgelis, Carmela Troncoso, Emiliano De Cristofaro, “Knock Knock, Who’s There? Membership Inference on Aggregate Location Data”, *25th Network and Distributed System Security Symposium (NDSS)*, 2018.

## Linear reconstruction attack

by A. Cohen, K. Nissim

**idea:** send queries targeting “random enough” sets of users and use the results to build a linear system, then reconstruct the database from it.

**based on:** Dinur, Irit, and Kobbi Nissim. "Revealing information while preserving privacy." *Proceedings of the twenty-second ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems*. ACM, 2003.

# Conclusions

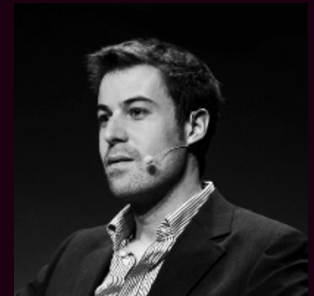
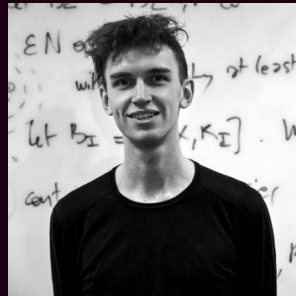
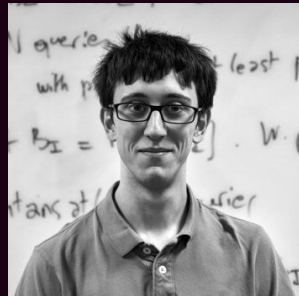
- Anonymization 👎 Data query systems 👍
- Relying on single mechanism is risky
- Defense-in-depth (e.g. query auditing, query rate limiting, etc.)

but also...

- alternatives to differential privacy are useful
- transparency is fundamental

---

# Thank you for your attention!



Find out more at: <https://cpg.doc.ic.ac.uk/blog/aircloak-diffix-signal-is-in-the-noise/>