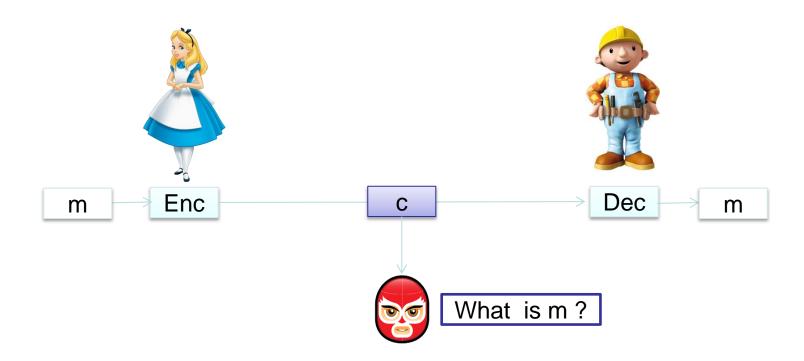


Privacy Preserving Data Collection and Analysis

Iraklis Leontiadis

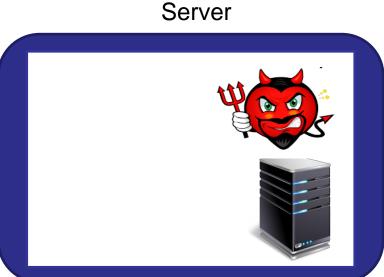
leontiad@eurecom.fr

The start

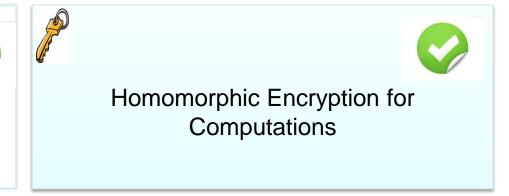


Nowadays









Outline

Generic problem Related work Shortcomings PP clustering PP ordering

Multi-User time-series data

Conclusion



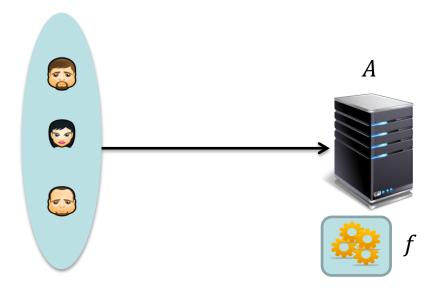
Problem











Energy forecasting

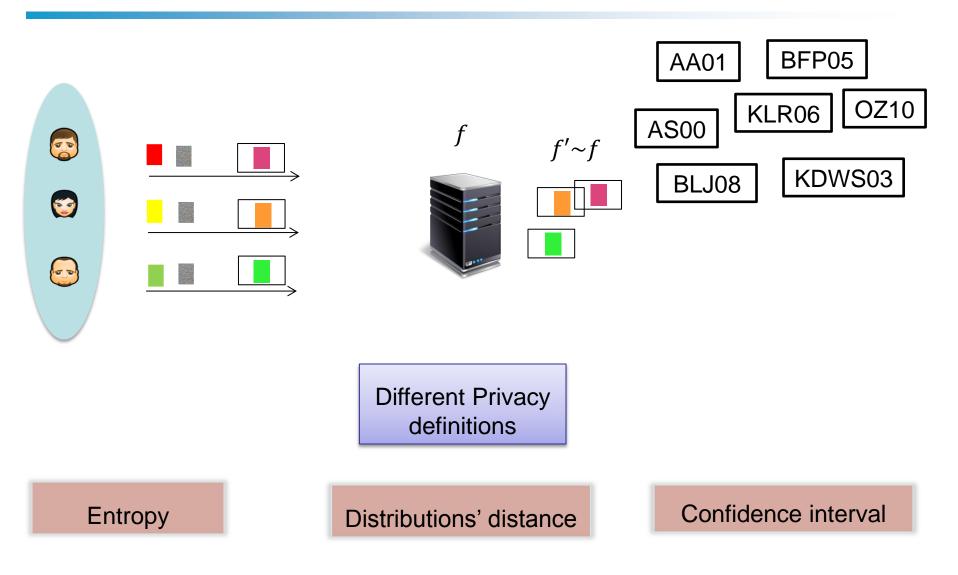
Medical data analysis

User Profiling

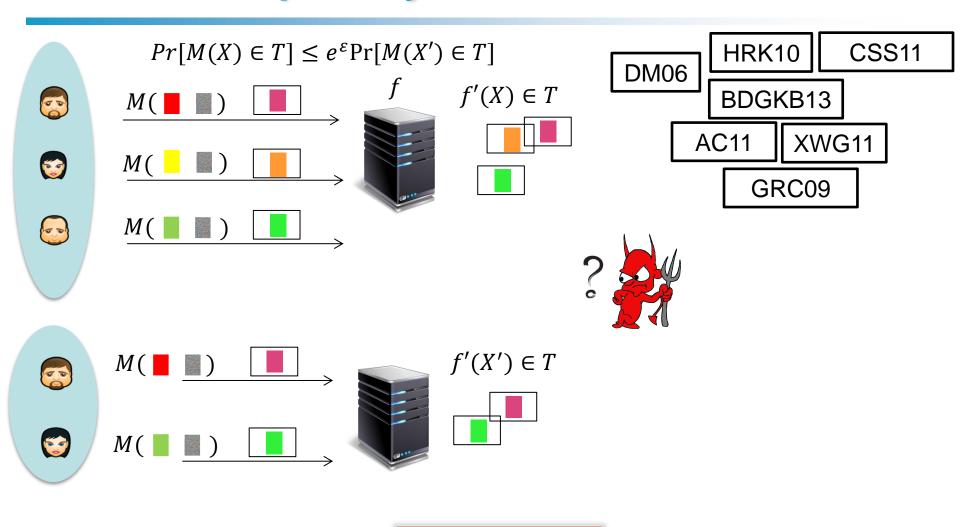
Overall Transactions



Ad-Hoc techniques



Differential privacy



Noisy *f*

Cryptographic solutions

Trusted Key Dealer

No support for dynamic population

JL2013

Intolerant to failures

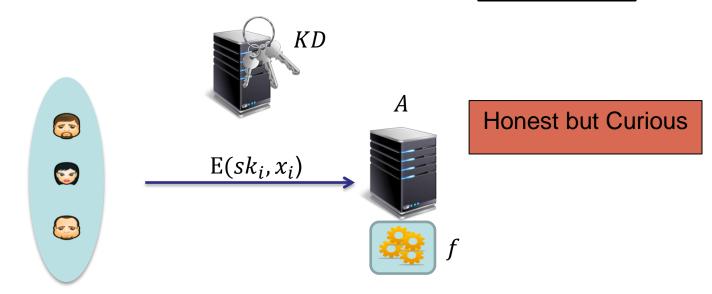
SCRCS2011

GMP2014

No Key Dealer

Communication cost

ET2012



Shortcomings with existing solutions

Noise-based

No accuracy

PPC

PPSGS

Encryption-based

- > Trusted key dealer
- Honest but curious Aggregator

PDTDA

PUDA

Outline

Generic problem Related work Shortcomings PP clustering PP ordering

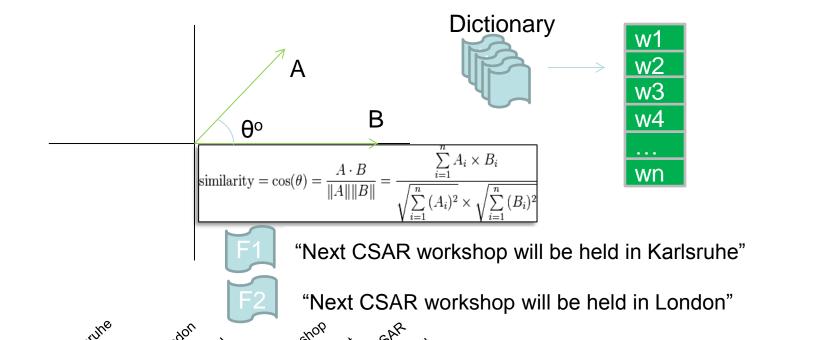
Multi-user time-series data

Conclusion



Privacy Preserving Clustering (PPC)

CSAR2013



 $\sigma = \frac{\sum Ai * Bi}{\sqrt{\sum Ai^2} * \sqrt{\sum Bi^2}} = 0.875$

Privacy Preserving Clustering (PPC)

Model:

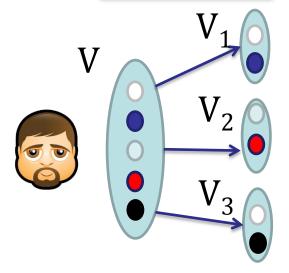
- Trustworthy users
- HbC Aggregator

Technique:

Cosine preserving transformations

Our solution

Dimension reduction



Random Scaling

$$S(r_1, V_1) = r_1 \cdot \bigcirc$$

$$S(r_2, V_2) = r_2 \cdot \bigcirc$$

$$S(r_3, V_3) = r_3 \cdot \bigcirc$$

Rotation

$$R_{\lambda^{\circ}}(r_1 \cdot V_1) = R_{\lambda^{\circ}} \cdot r_1 \cdot$$

$$\mathsf{R}_{\lambda^{\circ}}(\mathsf{r}_2 \cdot \mathsf{V}_2) = \mathsf{R}_{\lambda^{\circ}} \cdot \mathsf{r}_2 \cdot$$

$$R_{\lambda^{\circ}}(r_3 \cdot V_3) = R_{\lambda^{\circ}} \cdot r_3 \cdot \bigcirc$$



Clustering approach



Hierarchical Agglomerative clustering (HAC)

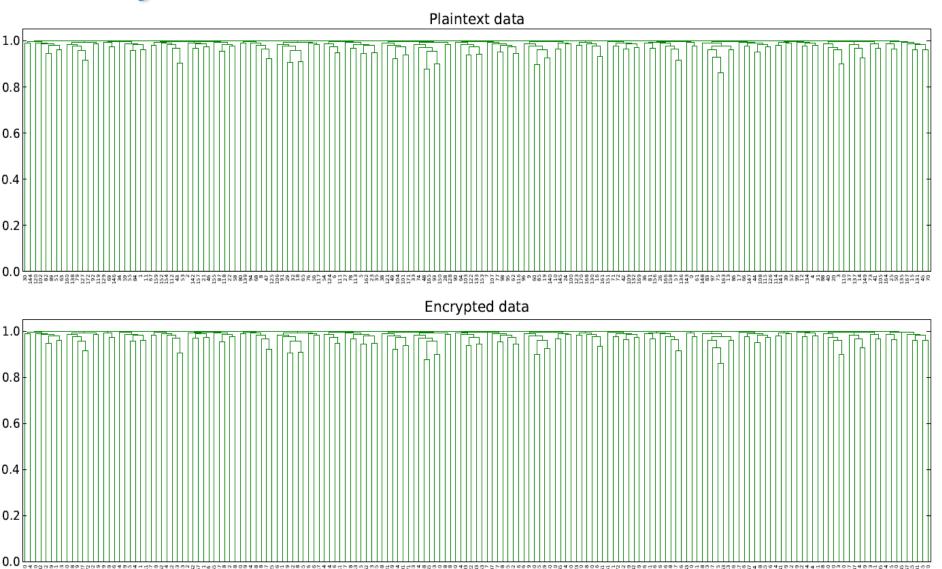
- Input: n points and N*N similarity matrix
- Output: Single cluster containing all n points

```
C=MakeSingletonClusters();
for i=0 to i=n:
   Find "closest" clusters c1,c2;
    Merge(c1,c2);
    RecomputeDistances(C);
   if #C=1 exit();
```

Agglomerative: O(n³)
Divisible: O(2ⁿ)

Cosine Similarity

Analysis



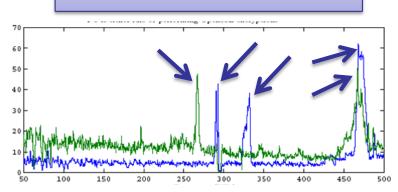
Privacy Preserving Smart Grid Statistics

(PPSGS)

DASEC2014

Provide accurate individual statistics

Obfuscate real values but reveal the order



Augment functionality by filtering spurious spikes



When did a home consume the maximum energy?

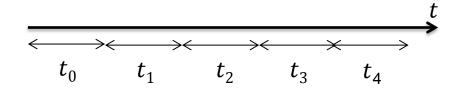


Promote awareness

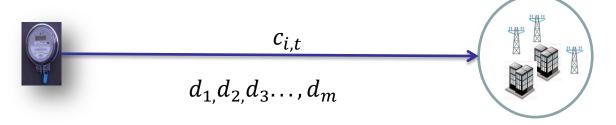


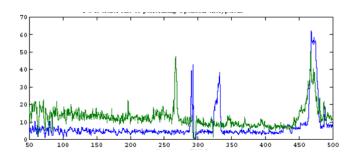
PPSGS

$$E_{OPE}(sk_{i}, x_{i,t}) = c_{i,t}$$



- MAX $(\{c_{i,t}\})$ at $t_{t'}$
- min interval = m





$$\sum_{t=1}^{m} d_t \stackrel{?}{=} 0$$

Analysis

Feasibility (1 day)

- Device [Texas Instruments MSP430 Microcontrollers]
- 16-bit RISC MSP430X MCU
- > 256KB Flash
- > 20 MHz clock rate
- > AES Accelerator

Period (seconds)	#Meterings	Flash(KB)	Time (Mcb)
1	86400	172.8	13.33
2	43200	86.4	6.32
3	28800	56.6	4.08
4	21600	43.2	2.99
5	17280	34.5	2.35
6	14400	28.8	1.93
7	12343	24.6	1.63
8	10800	21.6	1.41
9	9600	19.3	1.24
10	8640	17.2	1.10

Security

Reductionist proof from POPF-CPA



Outline

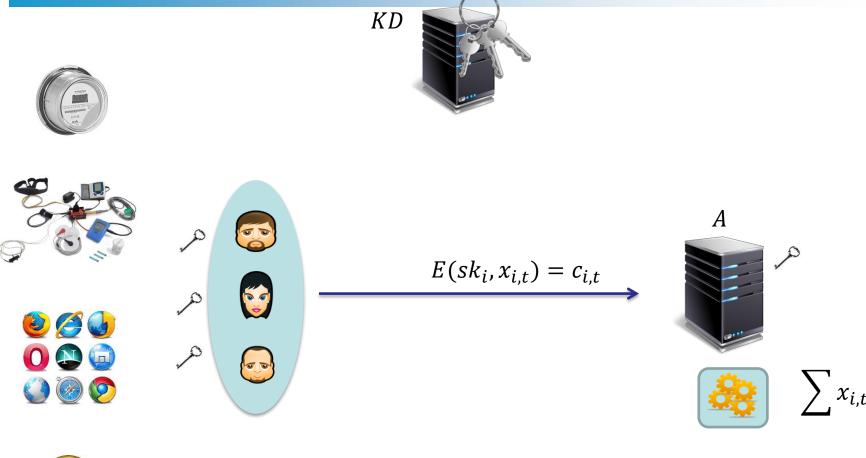
Generic problem Related work Shortcomings PP clustering PP ordering

Multi-user time-series data

Conclusion



Multi-user time series aggregation







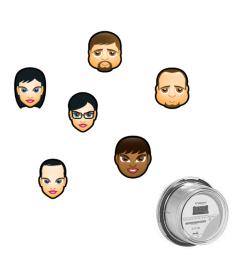
Shortcomings

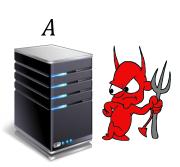
- Fully trusted key dealer
- No support for dynamic population
- Intolerant to failures
- Lack of a stronger security model



PDTDA









Private and Dynamic Time-Series Data Aggregation CANS 2014

Goals

- No trusted key dealer
- Dynamicity
- Resiliency to failures

Ideas

- User-generated keys
- > Responsibility splitting mechanism



JL2013

Setup(k):

- > N = pq for primes p, q (l the size of N)
- Trusted Dealer distributes:
 - secret keys sk_i ∈ {0,1}^{2l} to the users.
 - $\Im sk_0 = -\sum_{i=1}^n sk_i$ to the Aggregator.
 - $\mathcal{T}H(): \mathbb{Z}_N \to \mathbb{Z}_{N^2}^*$

• Encrypt($sk_i, x_{i,t}$):

 $> c_{i,t} = (1 + x_{i,t}N)H(t)^{sk_i} \mod N^2$

Aggregate:

$$\triangleright V_{t} = H(t)^{sk_0} \prod_{i=1}^{n} c_{i,t} = (1 + \sum_{i=1}^{n} x_{i,t} N) \mod N^2$$



PDTDA

 sk_2

$$aux_{i,t} = H(t)^{sk_A sk_i}$$

$$c_{i,t} = (1 + x_{i,t}N)H(t)^{sk_i} mod N^2$$

$$sk_A \in \mathbb{Z}_N^*$$

$$aux_{i,t}$$

$$aux_{i,t}$$

$$c_{i,t}$$

$$c_{i,t}$$

$$c_{i,t}$$

$$c_{i,t}$$

1.
$$P_t = \prod_{i=1}^n (c_{i,t})^{sk_A} = (1 + N \sum_{i=1}^n x_{i,t})^{sk_A} H(t)^{sk_A \sum_{i=1}^n x_{i,t}} \mod N^2$$

2.
$$I_t = \frac{\frac{P_t}{aux_t} - 1}{N}$$

3.
$$\sum_{i=1}^{n} x_{i,t} = I_t s k_A^{-1} \mod \mathbb{Z}_N$$



Privacy analysis

- Aggregator Obliviousness based on:
 - \triangleright DCR in $\mathbb{Z}_{N^2}^*$

- Collector Obliviousness based on:
 - \triangleright DCR in $\mathbb{Z}_{N^2}^*$
 - \triangleright QR in \mathbb{Z}_N^*
 - \triangleright DDH in the subgroup of QR in \mathbb{Z}_N^*

Benchmarks (sec)

Intel Core i5 CPU M 2430 @ 2.40GHz x4, 6GB

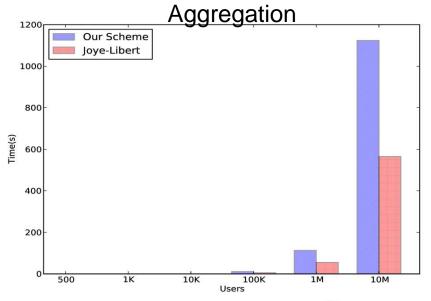


N Algorithm	2048	4096
Encrypt	0.116	0.4
Aux	0.123	0.44
Total	0.239	0.84

#Users Entity	500	1K	10K	100K	1M	10M
Collector	0.030	0.056	0.556	5.60	59.72	562.66
Aggregator	0.159	0.190	0.690	5.73	59.22	569.19

Encryption

Scheme N	Our scheme	Joye-Libert
2048	0.239	0.156
4096	0.84	0.4



Cubieboard ARM Cortex-A7 Dual-Core, 1GB



Private and Unforgeable Data Aggregation

CANS2015



















$$E(sk_i,x_{i,t})=c_{i,t}$$





Private and Unforgeable Data Aggregation

Goals

- Public Aggregate Verification
- Obliviousness
- Multi-user

Idea

- Homomorphic tags
- Homomorphic encryption

SCRCS2011

Setup(k):

- \triangleright \mathbb{G} a cyclic group with a generator g and prime order p
- > Trusted Dealer distributes:
 - $\text{ }^{\text{}}$ secret keys $\mathrm{sk}_{\mathrm{i}} \in \mathbb{Z}_{p}$.
 - $sk_0 = -\sum_{i=1}^n sk_i$ to the Aggregator.
 - $\mathcal{F}H():\{0,1\}^* \to \mathbb{G}$

• Encrypt($sk_i, x_{i,t}$):

$$\succ c_{i,t} = g^{x_{i,t}} H(t)^{sk_i} \in \mathbb{G}$$

Aggregate:

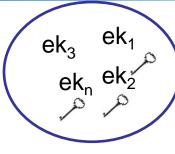
$$V = H(t)^{sk_0} \prod_{i=1}^n c_{i,t} = g^{\sum_{i=1}^n x_{i,t}} g \in \mathbb{G}$$

$$\sum_{i=1}^{n} c_i = \log_g(V)$$

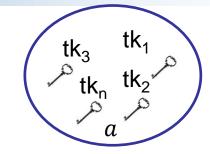


Private and Unforgeable Data Aggregation

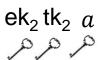
$$vk = g_2^{\sum_{i=1}^n tk_i}, g_2^a$$

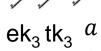








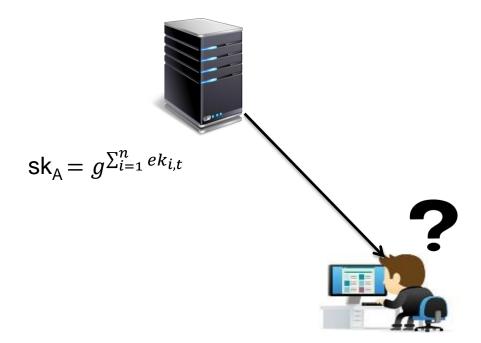












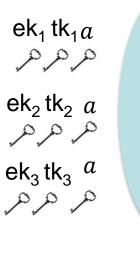


Private and Unforgeable Data Aggregation

$$vk = g_2^{\sum_{i=1}^n tk_i}, g_2^a$$

$$\sigma_t = \prod_{i=1}^n tag_{i,t} = H(t)^{\sum_{i=1}^n tk_i} g^{asum_t}$$

 sum_t, σ_t









$$c_{i,t} = g^{x_i} H(t)^{ek_i}$$

$$tag_{i,t} = g^{ax_{i,t}}H(t)^{tk_i}$$

$$\mathsf{sk}_{\mathsf{A}} = g^{\sum_{i=1}^{n} e k_{i,t}}$$

Constant verification time

$$e(\sigma_t, g_2) = e(H(t), g_2^{\sum_{i=1}^n tk_i})e(g^{sum_t}, g_2^a)$$



Security Analysis

- Aggregator Obliviousness based on:
 - > DDH

- Aggregate Unforgeability based on:
 - > BCDH
 - New LEOM assumption

Secure under GGM

Outline

Generic problem Related work Shortcomings PP clustering PP ordering

Multi-user time-series data

Conclusion



Recap

- New aggregation functions + accuracy
- No key dealer + dynamicity
- Verifiability

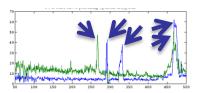
PPC

Dimension reduction Random Scaling

Rotation

PPSGS

OPE + differences



PDTDA

No key distribution

JL

CO



PUDA

Homomorphic Tags

Shi et al.





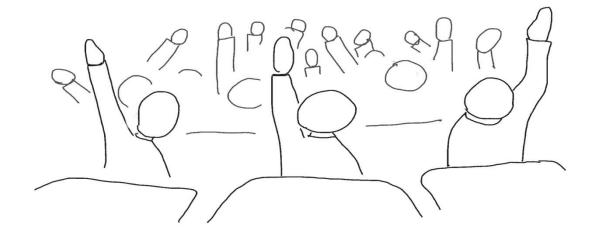
Future work

Verifiability in presence of untrustworthy users

Verifiability + No key dealer

Standard Model

Questions?



Thank you!!!