Practical privacy using homomorphic encryption – a myth or reality?

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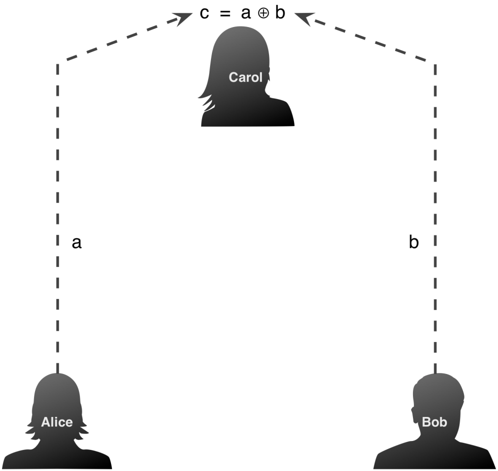
The magic of homomorphic encryption

1. Homomorphic encryption
   - What and why?
   - Application in recommender systems
2. Privacy preserving collaborative filtering (PPCF)
   - Collaborative filtering (CF), briefly
   - Privacy preserving Slope One
3. On the SaaS cloud
   - Google App Engine feasibility
   - An alternative approach
4. Tail piece
   - Conclusions and future avenues
   - Question time!

Compute blindly?



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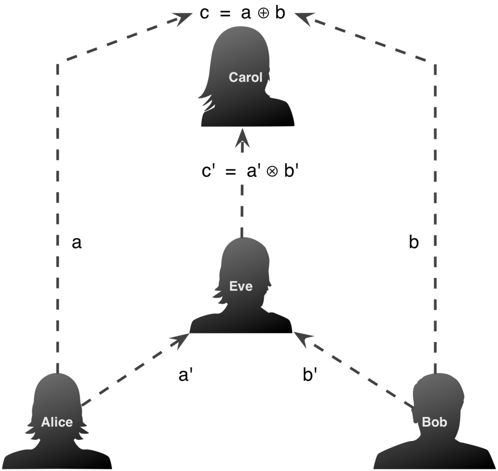

Compute blindly?

$$(m_1 \oplus m_2)' = m_1' \otimes m_2'$$

m_1 and m_2: plaintext messages; x': ciphertext of x; $\oplus$ and $\otimes$: two operations that satisfy this ***homomorphic*** relation.

Homomorphic cryptosystems

Depending on $\oplus$ and $\otimes$, we have:

- additive (e.g., Paillier, Damgärd-Jurik, Elliptic Curve ElGamal),
- multiplicative (e.g., RSA, ElGamal), and
- fully homomorphic cryptosystems (Craig Gentry et al.).

- too good to be true?

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- . . . and do so blindly?
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Application scenario

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CF – a form of recommendation

User-item rating data like this[1]:

	Canon 7D	Leica M9	Nikon D7000	...	Olympus OM-D
Alice	5	4	-	...	3
Bob	3	5	2	...	-
Carol	-	?	4	...	3
Dave	4	3	-	...	-

- The objective is to find a rating for Leica M9 for Carol.
- CF – a well-known recommendation technique, based on the preferences of the community.

[1] "-" indicates the absence of a rating.

CF – a form of recommendation

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Slope One predictors

Based on:

Lemire, D., Maclachlan, A. 2005. *Slope one predictors for online rating-based collaborative filtering*. In: Society for Industrial Mathematics.

Slope One predictors

- CF predictors of the form $f(x) = x + b$, hence "slope one".
- Simple and efficient (compared with SVD, PMCC, Cosine).

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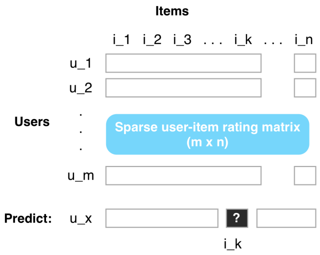

Figure: **The general CF problem.**

CF and Slope One

Pre-compute:

- ***Deviation matrix*** Δ: deviation of ratings of an item pair by the same user; dimension: $n \times n$.
- ***Cardinality matrix*** ϕ: number of co-existing ratings by the same user of an item pair; dimension same as Δ.

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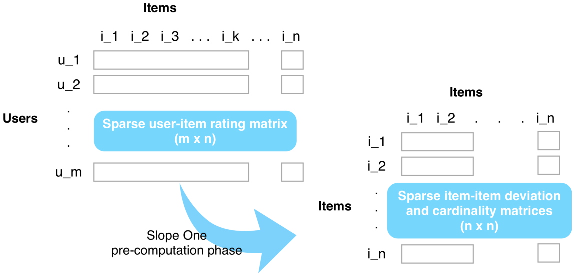

Figure: **Slope One pre-computation creates a 'model' which is used for prediction.**

The weighted Slope One predictor

- Average deviation:

$$\overline{\delta_{a,b}} = \frac{\Delta_{a,b}}{\phi_{a,b}} = \frac{\sum_i \delta_{i,a,b}}{\phi_{a,b}} = \frac{\sum_i (r_{i,a} - r_{i,b})}{\phi_{a,b}}$$

$\phi_{a,b}$: the number of the users who have rated both items; $\delta_{i,a,b} = r_{i,a} - r_{i,b}$: the deviation of the ratings of item a from that of item b both given by user i.

- The *weighted* Slope One predictor:

$$r_{u,x} = \frac{\sum_{a|a\neq x}(\overline{\delta_{x,a}} + r_{u,a})\phi_{x,a}}{\sum_{a|a\neq x}\phi_{x,a}} = \frac{\sum_{a|a\neq x}(\Delta_{x,a} + r_{u,a}\phi_{x,a})}{\sum_{a|a\neq x}\phi_{x,a}}$$

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Preserving privacy with Slope One CF

- An *additively homomorphic cryptosystem* – the Damgärd-Jurik cryptosystem, defining
  - homomorphic addition:

$$\mathcal{E}(m_1 + m_2) = \mathcal{E}(m_1) \cdot \mathcal{E}(m_2)$$

  - and homomorphic multiplication:

$$\mathcal{E}(m_1 \cdot \pi) = \mathcal{E}(m_1)^{\pi}$$

  m_1 and m_2 are plaintexts and π is a plaintext multiplicand.

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Privacy preserving weighted Slope One predictors

- The numerator of the prediction equation:

$$\sum_{a|a \neq x} (\Delta_{x,a} + r_{u,a}\phi_{x,a}) = \mathcal{D}(\prod_{a|a \neq x} (\mathcal{E}(\Delta_{x,a})(\mathcal{E}(r_{u,a})^{\phi_{x,a}})))$$

- The final prediction:

$$r_{u,x} = \frac{\mathcal{D}(\prod_{a|a \neq x}(\mathcal{E}(\Delta_{x,a})(\mathcal{E}(r_{u,a})^{\phi_{x,a}})))}{\sum_{a|a \neq x} \phi_{x,a}}$$

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- Pre-computed: $\mathcal{E}(\Delta)$ and ϕ.
- Encrypted query result decrypted using threshold decryption keys.
- Query answered by collaborating sites.
- Supports horizontal and vertical partitioning, using secure scalar product (Vaidya and Clifton).

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Some results

- **Hardware:** 2.53GHz Intel Core 2 Duo (dual core) processor, 8GB RAM, Mac OS X 10.6.7 and 64-bit Java 1.6.
- **Implementation:** Single server, single partition, MovieLens 100K dataset.

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Key size	Mean PC[a]	Total PC	Prediction
512 bits	30s	2h	500ms
1024 bits	90s	6h	1.5s
2048 bits	270s	18h	4.5s

[a] PC: pre-computation

Further reading

JISIS 2011 paper:

Basu, A., Vaidya, J., Kikuchi, H. 2011. *Efficient privacy-preserving collaborative filtering based on the weighted Slope One predictor*. In: Journal of Internet Services and Information Security (special edition).

Try this on the cloud

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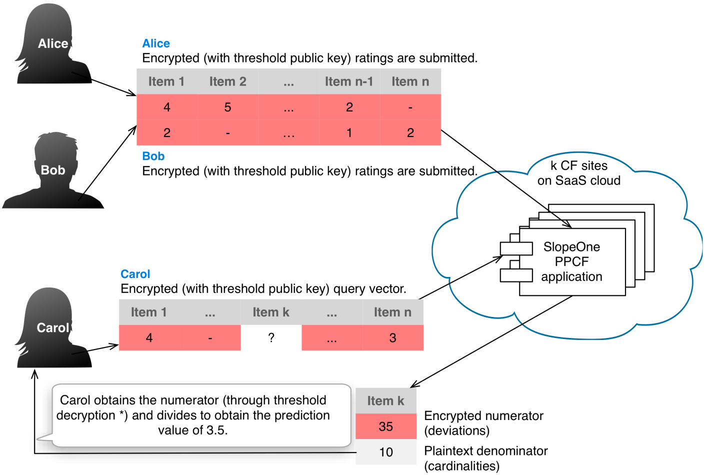

* Multiple PPCF sites compute the threshold decryption.

GAE/J challenges

- Servlet execution time limit (30s).
- High replication, slow access datastore.
- Lack of concurrency support (no threads!).
- Lack of control over resource allocation (bit better now with front-end instance classes).

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Further reading

ACM SAC 2012 paper:

Basu, A., Vaidya, J., Dimitrakos, T., Kikuchi, H. 2012. *Feasibility of a privacy preserving collaborative filtering scheme on the Google App Engine - a performance case study*. In Proc: 27th ACM Symposium on Applied Computing (SAC) Cloud Computing track, Trento.

An alternative PPCF on the GAE/J

- Identity anonymizer, plaintext deviation aggregation.
- No threshold decryption – user encrypts and decrypts.
- Prediction:

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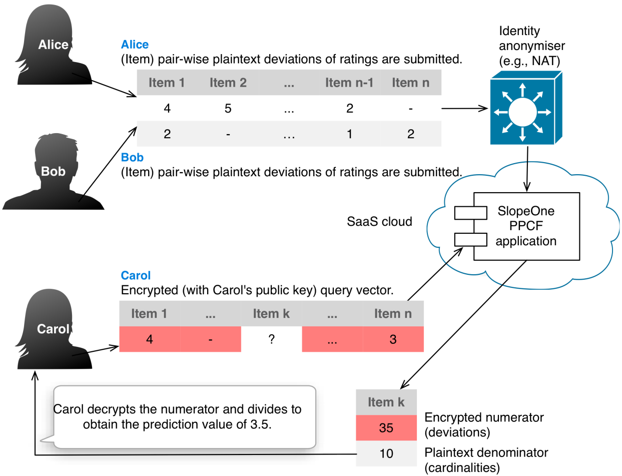
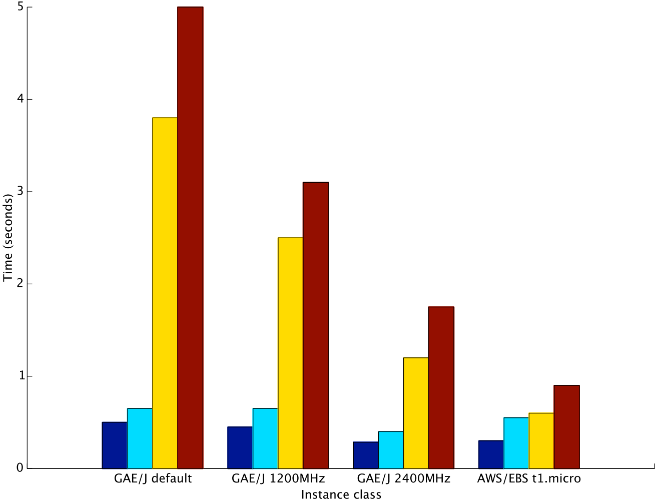


Results on the Google App Engine (GAE/J)

Bit size[a]	**Vector size**[b]	**Prediction time**
1024	5	500ms
1024	10	650ms
2048	5	3800ms
2048	10	5000ms

[a] Paillier cryptosystem modulus bit size, i.e. $|n|$.
[b] Size of the encrypted rating query vector.

Results: GAE/J and Amazon Elastic Beanstalk



Further reading

IEEE Cloudcom 2011 paper:

Basu, A., Vaidya, J., Kikuchi, H., Dimitrakos, T. 2011. *Privacy-preserving collaborative filtering for the cloud*. In Proc: 3rd IEEE International Conference on Cloud Computing Technology and Science (Cloudcom), Athens.

Let's wrap up

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Conclusions

Privacy with homomorphic encryption – worth it?

It works well in certain scenarios albeit some, mainly, performance issues.

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- Homomorphic encryption challenges: threshold decryption, computational complexity, supported operations.
- Application areas: privacy preserving data mining, graph problems e.g., resource allocation.
- Cloud applicability: performance, feasibility depends on type of application, platform.

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Privacy, cloud, responsibility and the future

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- Optimisation for computational complexity, power use – cloud infrastructure consumes power.
- Alternatives – open question?

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Thank you for listening!

Any questions?