Practical privacy preserving collaborative filtering on the Google App Engine

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CSS 2011, Niigata, Japan

Table of Contents

Recommendation

We often have user-item rating data similar to this:

	Virgin Atlantic	Emirates	Singapore Airlines
Alice	3	?	5
Bob	3	4	5
Tracy	-	2	4
Steve	3	3	-

- The objective is to recommend the rating for Emirates to Alice using collaborative filtering (CF).
- CF can be either memory based using similarity or deviations between users (user-based) or items (item-based); or be model based, such as the singular value decomposition.

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- A recommendation example: Amazon's "people who buy **x** also buy **y**".
- Recommendation providers (e.g. Amazon, eBay) run on cloud computing infrastructures.
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Compute a rating prediction through privacy preserving CF on a Platform-as-a-Service (PaaS) cloud. Requirements are:

- to hide user's private rating data without depending any trusted third party for threshold decryption,
- to assume honest user,
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Can we predict ratings for the user from some incrementally pre-computed compact model instead of users' private rating data?

- Traditional user-based or item-based CF requires storage of private rating data; easy to update but slow to query.
- Low-rank matrix approximations (e.g. SVD) are difficult to compute incrementally; slow to update but fast to query.
- Slope One (I will explain soon!) uses an incrementally updatable item-item matrix model; fast to update and fast to query.

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Our contributions

- We propose a privacy preserving SlopeOne CF on the Google App Engine for Java (GAE/J)[1] – a specialised SaaS construction PaaS cloud.
- Proposed scheme can be extended to vertical partitions.
- Feasible on a real world public cloud; also tested with Amazon Web Services Elastic Beanstalk (AWS EBS)[2] PaaS cloud.

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The extension of our work

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What is Slope One?

The original paper on SlopeOne CF:

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

- Item-based collaborative filtering (CF) scheme of the form $f(x) = x + b$, hence "slope one".
- Weighted version is based on pre-computed average deviations between ratings of items, weighted by relative cardinalities of pairs of items.
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Generalising the rationale

- The average deviations of ratings from item a to item b is given as:

$$\overline{\delta_{a,b}} = \frac{\Delta_{a,b}}{\phi_{a,b}} = \frac{\sum_i \delta_{i,a,b}}{\phi_{a,b}} = \frac{\sum_i (r_{i,a} - r_{i,b})}{\phi_{a,b}} \quad (1)$$

  where $\phi_{a,b}$ is the count of the users who have rated both items while $\delta_{i,a,b} = r_{i,a} - r_{i,b}$ is the deviation of the rating of item a from that of item b both given by user i.

- Thus, the rating for user u and item x using the *weighted* Slope One is predicted as:

$$r_{u,x} = \frac{\sum_{a|a \neq x} (\overline{\delta_{x,a}} + r_{u,a}) \phi_{x,a}}{\sum_{a|a \neq x} \phi_{x,a}} = \frac{\sum_{a|a \neq x} (\Delta_{x,a} + r_{u,a} \phi_{x,a})}{\sum_{a|a \neq x} \phi_{x,a}} \quad (2)$$

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Weighted Slope One predictor has the following two pre-computed matrices.

- ***Deviation matrix*** or Δ: each element is the total deviation of ratings between a pair of items, calculated over cases where both items have been rated by the same user. If the ratings matrix is of dimension *mxn* (i.e. *n* items) then Δ is of dimension *nxn*.
- ***Cardinality matrix*** or ϕ: each element is the count of the cases where items in a pair have been both rated by the same user. It is of the same dimension as Δ.

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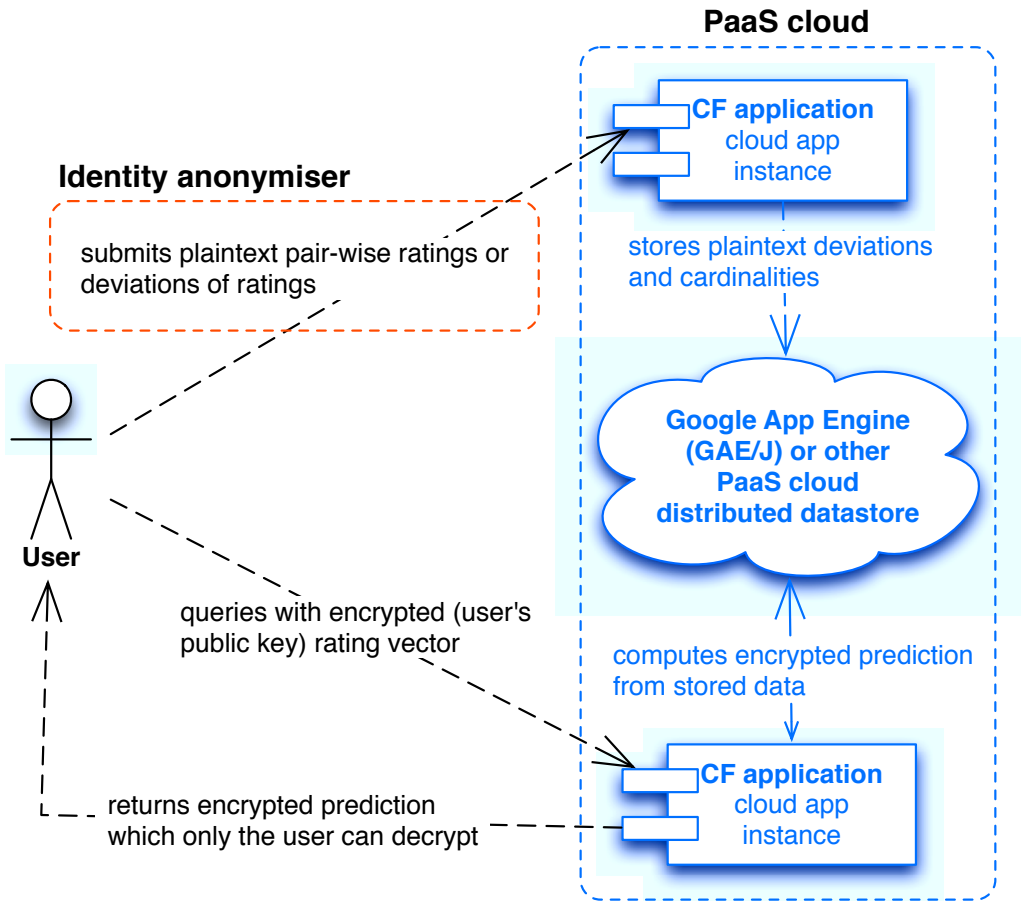

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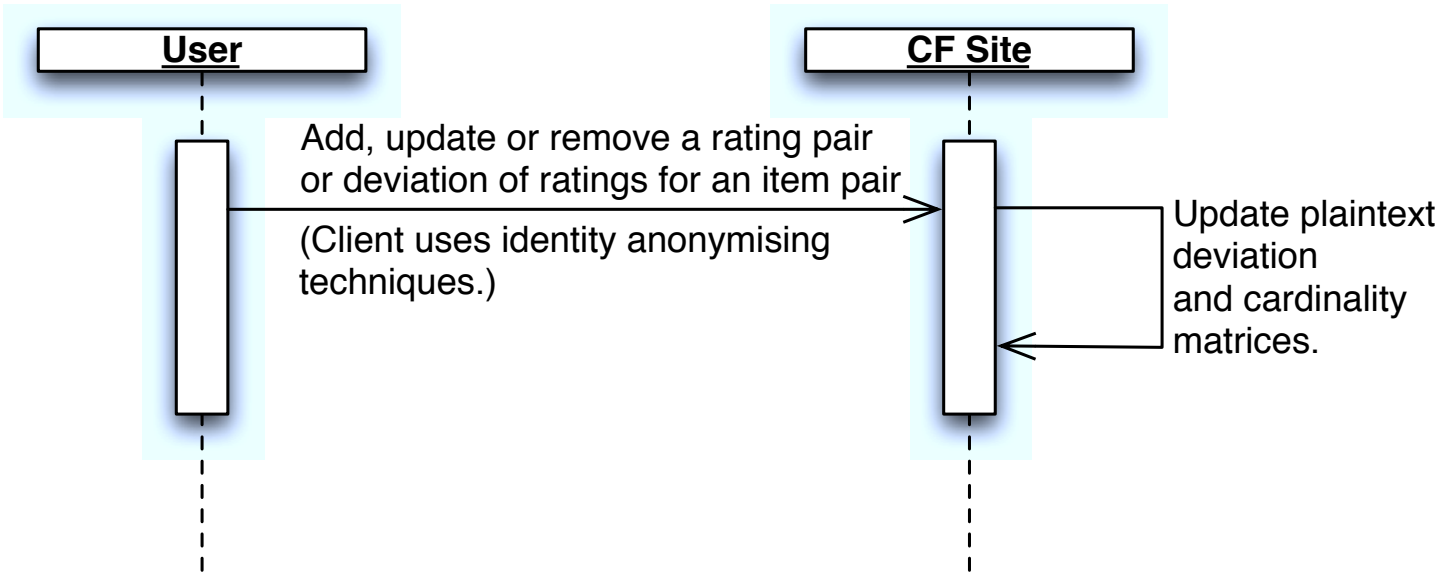

Figure: **UML sequence diagram for addition, update or deletion of data between any one user and the cloud-based CF site.**

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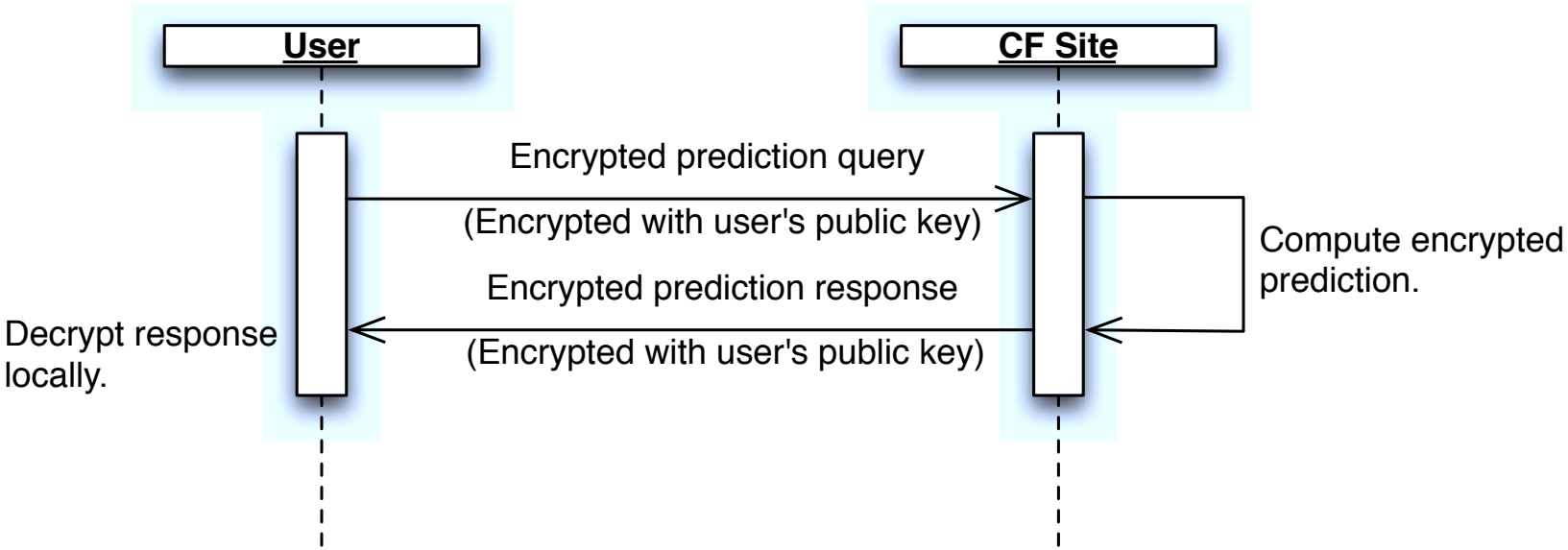

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Privacy preserving Slope One CF

Additively homomorphic cryptosystem (Paillier) supports:

- homomorphic addition:

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

- homomorphic multiplication:

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

We denote encryption and decryption functions as $\mathcal{E}()$ and $\mathcal{D}()$ respectively with plaintext messages m_1, m_2 and integer multiplicand π.

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Based on the previous equation for plaintext Slope One predictors, we can write:

$$\sum_{a|a\neq x}(\Delta_{x,a}+r_{u,a}\phi_{x,a}) = \mathcal{D}(\prod_{a|a\neq x}(\mathcal{E}(\Delta_{x,a})(\mathcal{E}(r_{u,a})^{\phi_{x,a}}))) \quad (3)$$

and reducing the number of encryptions, the final prediction is given as:

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Google App Engine for Java (GAE/J) features:

- Automatically allocated scalable resources for growing user requests.
- Slow high replication datastore access but fast distributed in-memory cache.
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Table: Comparison of typical prediction timings with the Google App Engine (on a good day!)

Bit size[a]	**Vector size**[b]	**Prediction time**[c]
1024	5	410ms
1024	10	825ms
2048	5	1900ms
2048	10	3500ms

[a] Paillier cryptosystem modulus bit size, i.e. $|n|$.

[b] Size of the encrypted rating vector.

[c] Our experiments with the Amazon Elastic Beanstalk show that EBS is substantially faster.

Demo

- Google App Engine implementation: `http://gaejppcf.appspot.com/`.
- Amazon Elastic Beanstalk implementation: `http://gaejppcf.elasticbeanstalk.com/`.
- Simulated attack on private data: in both cases, the cloud application tracks user's IPv4 address – a typical attack scenario to attempt to link ratings to users. But this fails to conclusively link ratings to users even when using a simple IPv4 NAT.

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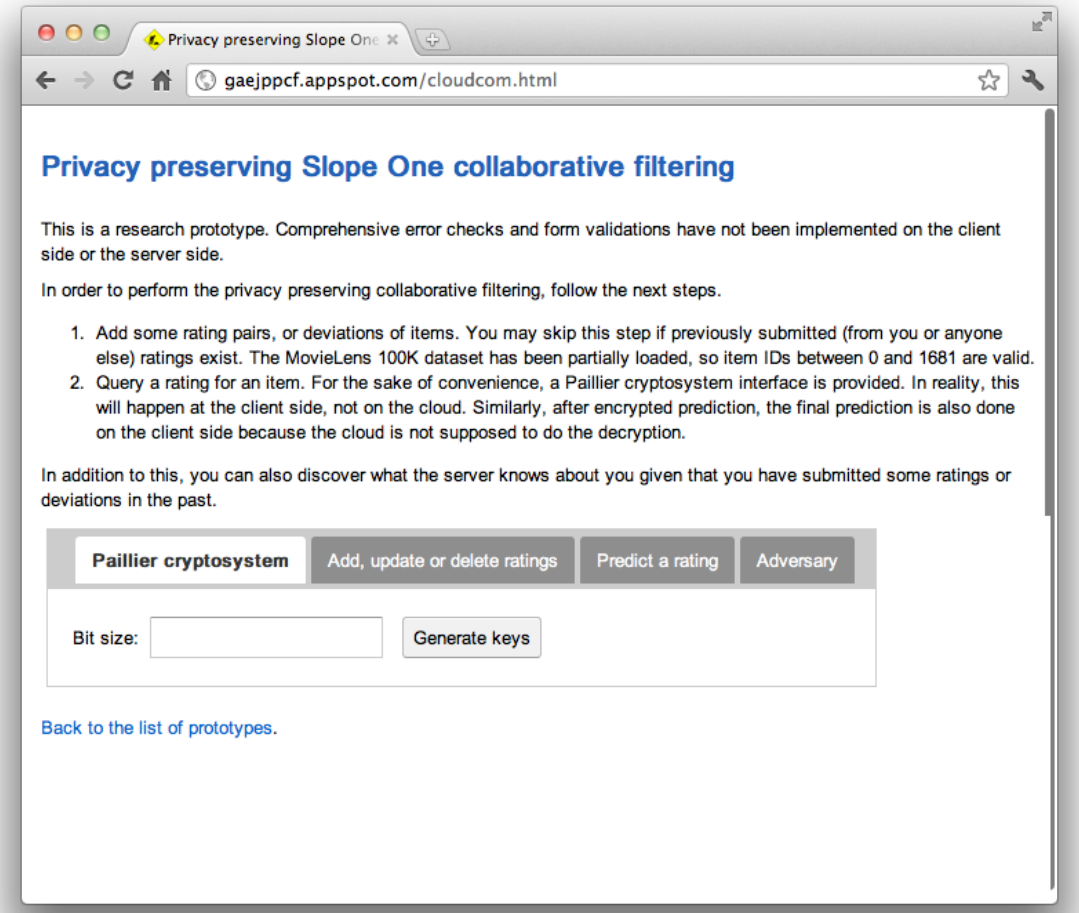

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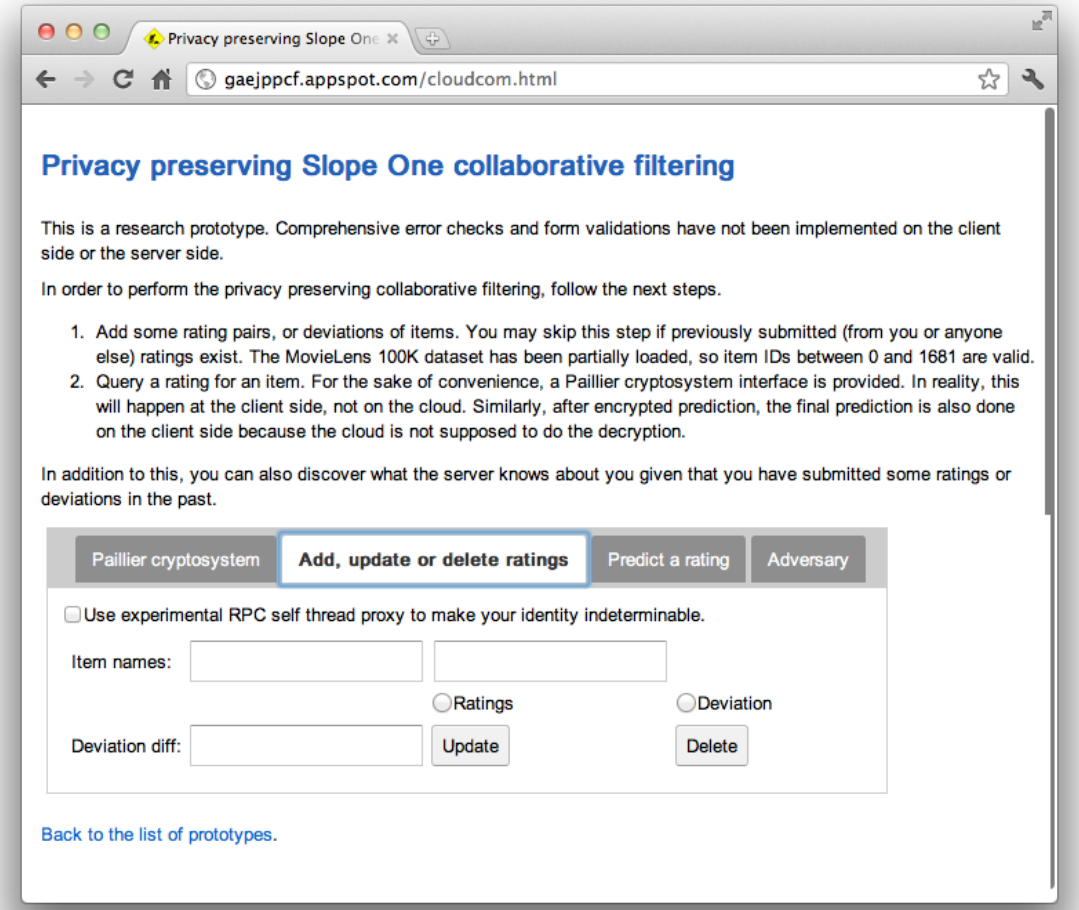

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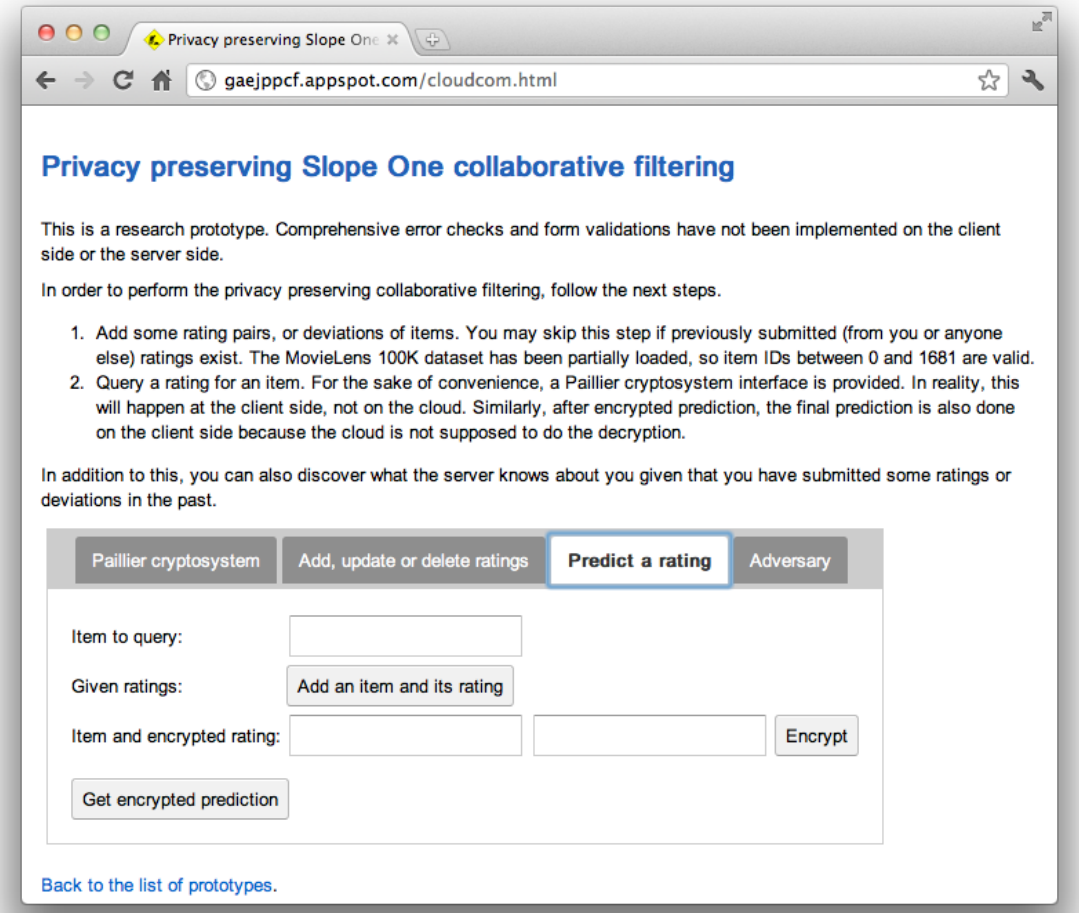
Prediction query:



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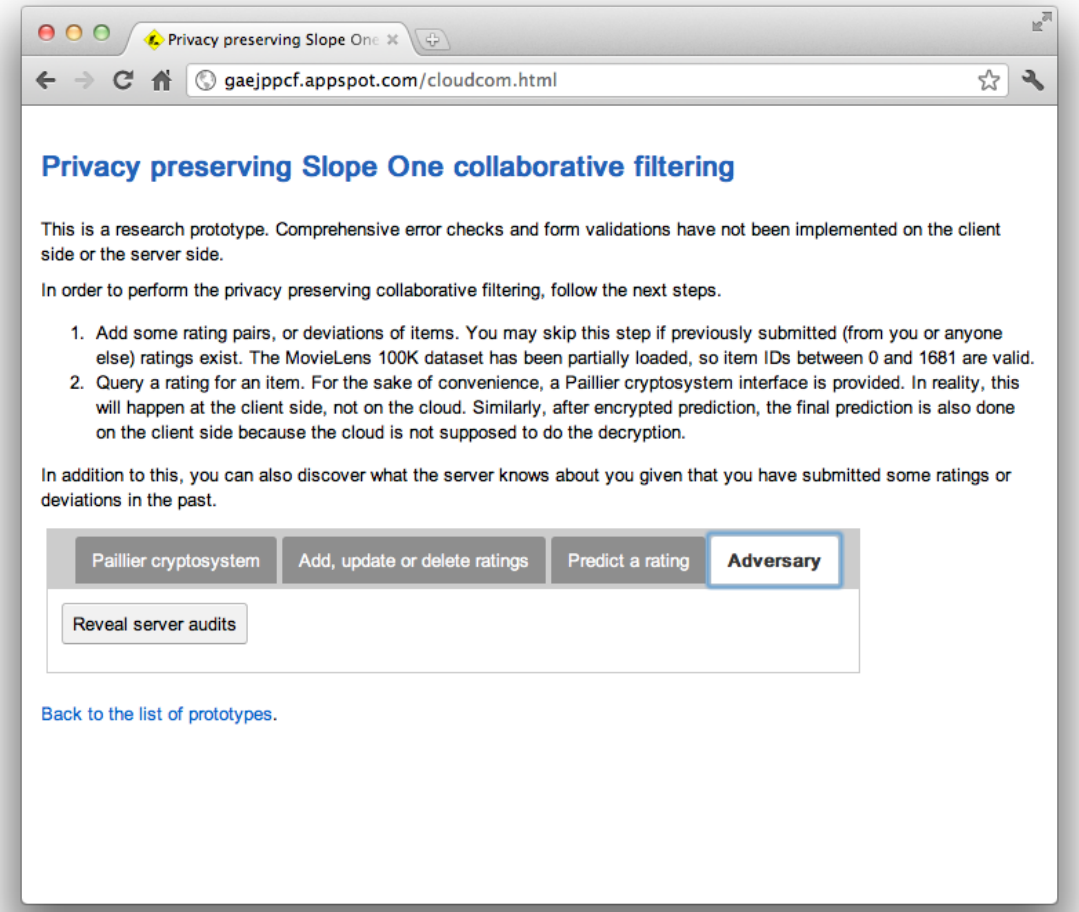
Adversary:



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Thank you for listening!

Any questions?