

technologies





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The elementary blocks of data analysis



The elementary blocks of data analysis



The elementary blocks of data analysis



How to guarantee outputs are anonymous?

1/ Remove PII?



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The fields are likely to be unique and easy to match to individuals

=> REMOVE

This combination of fields is probably unique, but it would be bad luck if someone uses it to identify someone.

=> KEEP

1/ Remove PII



Robust De-anonymization of Large Datasets (How to Break Anonymity of the Netflix Prize Dataset)

Arvind Narayanan and Vitaly Shmatikov

The University of Texas at Austin

2007

Nov

22

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Abstract

We present a new class of statistical de-anonymization attacks against high-dimensional micro-data, such as individual preferences, recommendations, transaction records and so on. Our techniques are robust to perturbation in the data and tolerate some mistakes in the adversary's background knowledge. We apply our de-anonymization methodology to the Netflix Prize dataset, which contains anonymous movie ratings of 500,000 subscribers of Netflix, the world's largest online movie rental service. We monstrate that an adversary who knows only a little bit about an individual subscriber can easily subscriber's record in the dataset. Using the Internet Movie Database as the source of CR bet a record in the dataset. Using the include records of known users, uncovering their the successfully identified the Netflix records of known users, uncovering their and other potentially sensitive information. NetFilx Cancels Recommendation + CS. 0105v2 ≈ MIBED , are increasingly becoming h. Some datasets , BACKCHANNEL BUSINESS CULTURE GEAR IDEAS MORE V RYAN SINGEL SECURITY 03.12.2010 02:40 PM * 10 0 NetFlix Cancels Recommendation Contest After Privacy Lawsuit Netflix is canceling its second \$1 million Netflix Prize to settle a legal Nethix is canceling its second \$1 million Nethix Frize to settle a legal challenge that it breached customer privacy as part of the first contest's non-for a bottor movie-recommendation and in Gridau's and incoments Chailenge that it preached customer privacy as part of the first contests race for a better movie-recommendation engine. Friday's announcement race for a better movie-recommendation engine. Friday's announcement Came five months after Netflix had announced a successor to its algorithms improvided to its algorithms Came five months after Netflix had announced a successor to its algorit improvement contest. The company at the time said it intended to [...]

2/ Aggregate?

- As long as there are unique rows, there is re-identification risk
- Aggregation does improve things <u>but</u>:
 - It destroys most of the potential for machine learning
 - It is not a silver bullet and can still lead to re-identification (triangulation?)
 - It requires ad hoc decision making

=> Sharing 'anonymous' data is probably an illusion

A "mathematical" definition of anonymous information

"Anonymous information: information which does not relate to an identified or identifiable natural person."

"Data which could be attributed to a natural person by the use of additional information should be considered to be information on an identifiable natural person". (<u>GDPR, Recital 26</u>)

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=> I should not learn something on any given individual
=> It should not depend on what I already know

A mathematical definition of anonymous information: *Differential privacy*

An algorithm A is (ε, δ) -differentially private if for any two neighboring datasets D and D' and any event S:

$\Pr[\mathcal{A}(\mathcal{D}) \in \mathcal{S}] \le e^{\epsilon} \Pr[\mathcal{A}(\mathcal{D}') \in \mathcal{S}] + \delta$

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 $\Pr[\mathcal{A}(\{\text{data}, \mathbf{A}\}) = s] \approx \Pr[\mathcal{A}(\{\text{data}, \mathbf{A}\}) = s]$

Not quite sharing "data"



Not quite sharing "data"



- Any data, no matter how sensitive
- Any learning objective
- No assumption on what information may be used

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Sarus: Learn from Data You cannot See with Privacy Guarantees



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