Formal Privacy Analyses for Open Banking

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- Facilitates access to new financial products or services
- Smaller fintechs can evaluate customers without requiring negotiation with other banks or relying on customer-provided information

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    - Are mandatory and are used by companies in multiple ways
    - Carry way more information than what companies need
    - May contain a variety of sensitive information
- Goal: Assess privacy risks involved when sharing financial data via Open Banking

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	Re-identification Risk			
Auxiliary Information	1 month	2 months	3 months	4 months
Date, Payee, Category				
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Auxiliary Information	1 month	2 months	3 months	4 months
Date, Payee, Category	5.30%			
Date, Amount	26.6%			
Date, Payee, Amount	52.1%			
Date, Amount, Category	43.7%			
Date, Payee, Amount, Category	54.4%			

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Auxiliary Information	1 month	2 months	3 months	4 months
Date, Payee, Category	5.30%	29.2%		
Date, Amount	26.6%	80.7%		
Date, Payee, Amount	52.1%	91.1%		
Date, Amount, Category	43.7%	91.7%		
Date, Payee, Amount, Category	54.4%	93.6%		

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	Re-identification Risk			
Auxiliary Information	1 month	2 months	3 months	4 months
Date, Payee, Category	5.30%	29.2%	60.9%	
Date, Amount	26.6%	80.7%	97.5%	
Date, Payee, Amount	52.1%	91.1%	99.2%	
Date, Amount, Category	43.7%	91.7%	99.4%	
Date, Payee, Amount, Category	54.4%	93.6%	99.6%	

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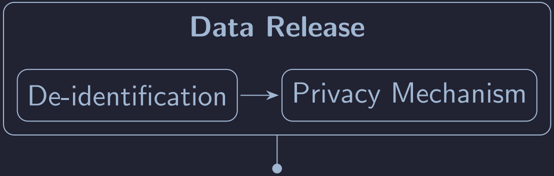
	Re-identification Risk			
Auxiliary Information	1 month	2 months	3 months	4 months
Date, Payee, Category	5.30%	29.2%	60.9%	83.6%
Date, Amount	26.6%	80.7%	97.5%	99.8%
Date, Payee, Amount	52.1%	91.1%	99.2%	99.9%
Date, Amount, Category	43.7%	91.7%	99.4%	100%
Date, Payee, Amount, Category	54.4%	93.6%	99.6%	100%

Formal Model — Attacks Against Data Releases



Data Release

De-identification

Privacy Mechanism

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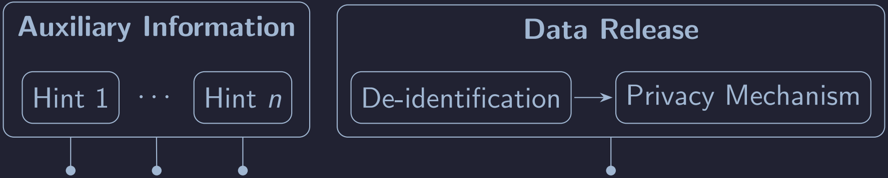

Auxiliary Information

Hint 1 · · · Hint n

Data Release

De-identification → Privacy Mechanism

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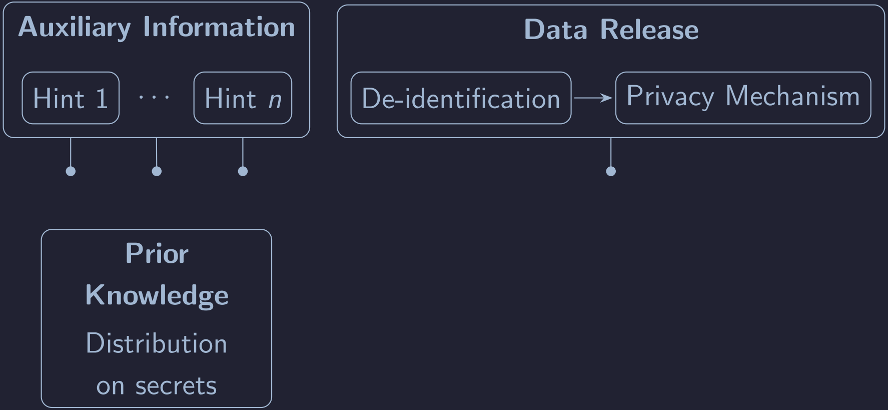

Auxiliary Information

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Data Release

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Prior Knowledge

Distribution on secrets

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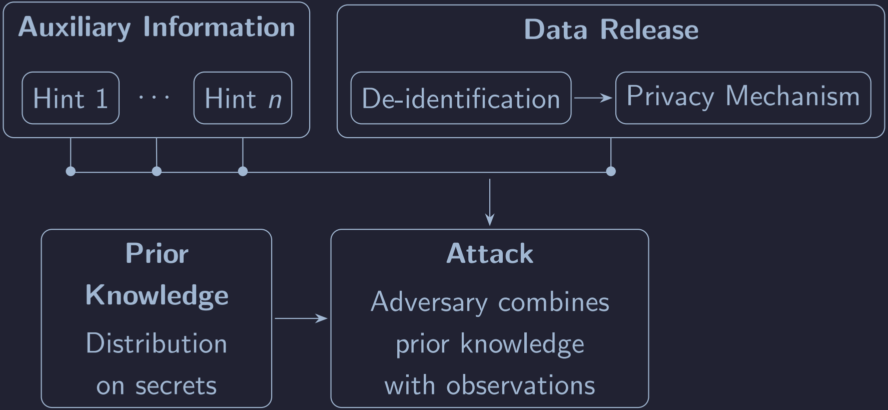

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Adversary combines prior knowledge with observations

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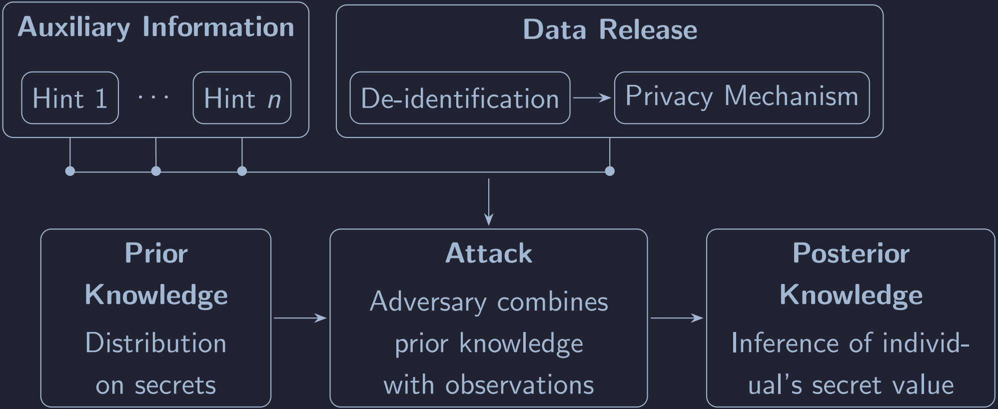

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Posterior Knowledge

Inference of individual's secret value

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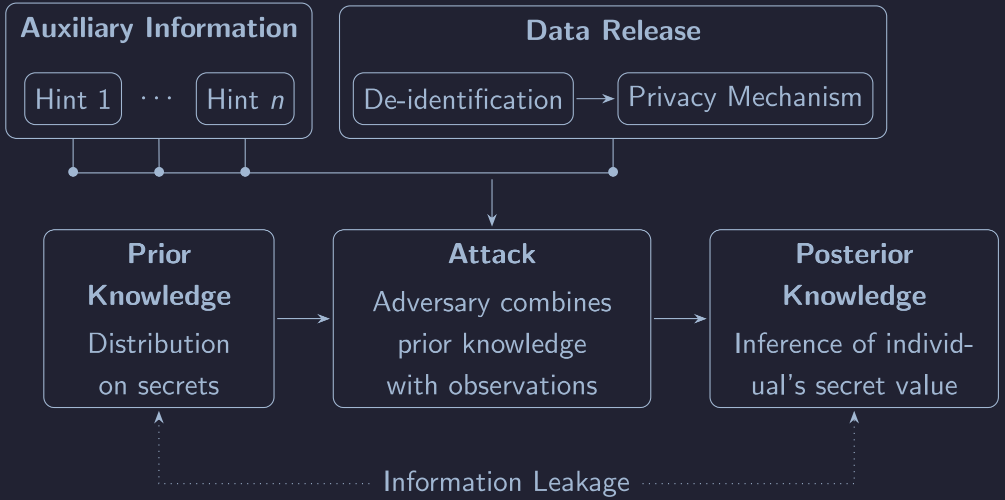

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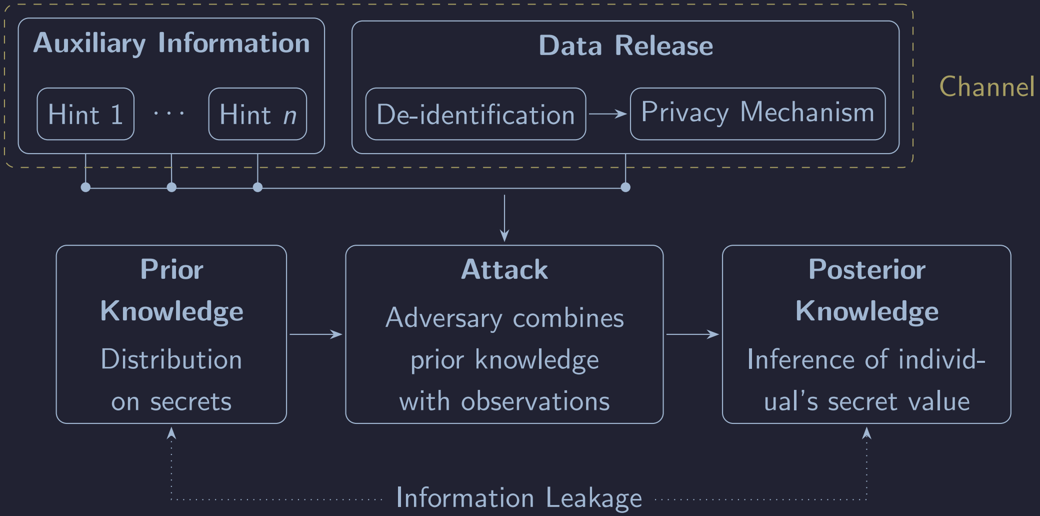

Auxiliary Information

Hint 1 · · · Hint n

Data Release

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Channel

Prior Knowledge

Distribution on secrets

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Adversary combines prior knowledge with observations

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Formal Model — Modelling with Channels

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$$\begin{tikzcd}
x_1 = \langle \text{Lineu}\colon \vec{t}_1, \text{Nenê}\colon \vec{t}_2, \text{Agostinho}\colon \vec{t}_3, \text{Tuco}\colon \vec{t}_4, \text{Bebel}\colon \vec{t}_5 \rangle \arrow[dr] & \\
& d
\end{tikzcd}$$

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\end{tikzcd}$$

- In addition to observing a de-identified dataset d, an attacker might also know that their target, say Lineu, recurringly buys at a Pastry Shop and Araujo
- With 2 months of data, the attacker could observe, e.g., $\langle \text{Pastry Shop}, \text{Araujo}, d \rangle$

Formal Model — Modelling with Channels

$$\begin{array}{c c c c c} C^{\text{Lineu}} & \langle\text{Pastry}, \text{Araujo}, d\rangle & \langle\text{Clinic}, \text{Araujo}, d\rangle & \langle\text{Clinic}, \text{Pastry}, d\rangle & \cdots \\ x_1 & \frac{1}{2} & \frac{1}{2} & 0 & \cdots \\ x_2 & 0 & 0 & 0 & \cdots \\ x_3 & 0 & \frac{1}{6} & \frac{1}{6} & \cdots \\ x_4 & 0 & 0 & 0 & \cdots \\ x_5 & 0 & 0 & 0 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \end{array}$$

Formal Model — Modelling with Channels — Compositions

We can decompose the final channel $\mathsf{C}^{\mathsf{Lineu}}$ into subchannels, each corresponding to one of the subcomponents (hints and data release): $\mathsf{H}^1 \parallel \mathsf{H}^2 \parallel \mathsf{D}$, where

$$(\mathsf{A} \parallel \mathsf{B})_{x,\langle y,z\rangle} \overset{\text{def}}{=} \mathsf{A}_{x,y}\, \mathsf{B}_{x,z}$$

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$$\begin{array}{c|cccccc|}
\mathrm{H}^1 & \text{Pastry} & \text{Clinic} & \text{Araujo} & \text{Uber} & \text{Ibis} & \cdots \\
x_1 & \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 & \cdots \\
x_2 & 0 & 0 & 1 & 0 & 0 & \cdots \\
x_3 & 0 & \frac{1}{3} & 0 & \frac{1}{3} & \frac{1}{3} & \cdots \\
x_4 & 0 & 0 & 0 & 1 & 0 & \cdots \\
x_5 & 0 & 0 & 0 & 1 & 0 & \cdots \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots
\end{array}
\parallel
\begin{array}{c|cccc|}
\mathrm{H}^2 & \text{Araujo} & \text{Transfer} & \text{Pastry} & \cdots \\
x_1 & 1 & 0 & 0 & \cdots \\
x_2 & 0 & 1 & 0 & \cdots \\
x_3 & \frac{1}{2} & 0 & \frac{1}{2} & \cdots \\
x_4 & 1 & 0 & 0 & \cdots \\
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\end{array}
\parallel
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\mathrm{D} & d & d_2 & \cdots \\
x_1 & 1 & 0 & \cdots \\
x_2 & 1 & 0 & \cdots \\
x_3 & 1 & 0 & \cdots \\
x_4 & 1 & 0 & \cdots \\
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- An adversary with a particular target, say Lineu, is modelled as

$$\mathbf{1}_{\text{Lineu}}(w, x) \overset{\text{def}}{=} 1 \text{ if } w = x\texttt{@Lineu} \text{ else } 0,$$

  where x`@Lineu` returns the record labelled as Lineu in x

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- The adversary computes a distribution on the possible outputs as

$$(\pi \triangleright \mathsf{C})_y \overset{\text{def}}{=} \sum_{x \in \mathcal{X}} (\pi \triangleright \mathsf{C})_{x,y} = \sum_{x \in \mathcal{X}} \pi_x \, \mathsf{C}_{x,y}$$

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- And distributions on the possible secret values, conditioned on outputs, as

$$(\pi \triangleright \mathrm{C})_{x|y} \stackrel{\text{def}}{=} \frac{(\pi \triangleright \mathrm{C})_{x,y}}{(\pi \triangleright \mathrm{C})_y} = \frac{\pi_x \, \mathrm{C}_{x,y}}{(\pi \triangleright \mathrm{C})_y}$$

Formal Model — **Quantifying Leakage**

- Then, the (expected) posterior g-vulnerability is

$$V_g[\pi \triangleright \mathsf{C}] \overset{\text{def}}{=} \sum_{y \in \mathcal{Y}} (\pi \triangleright \mathsf{C})_y \, V_g((\pi \triangleright \mathsf{C})_{X|y})$$

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- In our running example, $g = \mathbf{1}_{\text{Lineu}}$ and $\mathsf{C} = \mathsf{C}^{\text{Lineu}} = \mathsf{H}^1 \parallel \mathsf{H}^2 \parallel \mathsf{D}$

Formal Model — **Quantifying Leakage**

$$
\begin{array}{cc}
\pi & \\
\begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ \vdots \end{matrix} &
\begin{bmatrix} \frac{1}{|\mathcal{X}|} \\ \frac{1}{|\mathcal{X}|} \\ \frac{1}{|\mathcal{X}|} \\ \frac{1}{|\mathcal{X}|} \\ \frac{1}{|\mathcal{X}|} \\ \vdots \end{bmatrix}
\end{array}
[\triangleright]
\begin{array}{cc}
\mathsf{C}^{\mathsf{Lineu}} & \begin{matrix} \langle \text{Pastry, Araujo}, d\rangle & \langle \text{Clinic, Araujo}, d\rangle & \cdots \end{matrix} \\
\begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ \vdots \end{matrix} &
\begin{bmatrix} \frac{1}{2} & \frac{1}{2} & \cdots \\ 0 & 0 & \cdots \\ 0 & \frac{1}{6} & \cdots \\ 0 & 0 & \cdots \\ 0 & 0 & \cdots \\ \vdots & \vdots & \vdots \end{bmatrix}
\end{array}
=
\begin{array}{cc}
 & \begin{matrix} \frac{4!}{2|\mathcal{X}|}\,\langle \text{Pastry, Araujo}, d\rangle & \frac{2\cdot 4!}{3|\mathcal{X}|}\,\langle \text{Clinic, Araujo}, d\rangle & \cdots \end{matrix} \\
\begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ \vdots \end{matrix} &
\begin{bmatrix} \frac{1}{4!} & \frac{3}{4\cdot 4!} & \cdots \\ 0 & 0 & \cdots \\ 0 & \frac{1}{4\cdot 4!} & \cdots \\ 0 & 0 & \cdots \\ 0 & 0 & \cdots \\ \vdots & \vdots & \vdots \end{bmatrix}
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$$

Formal Model — Quantifying Leakage

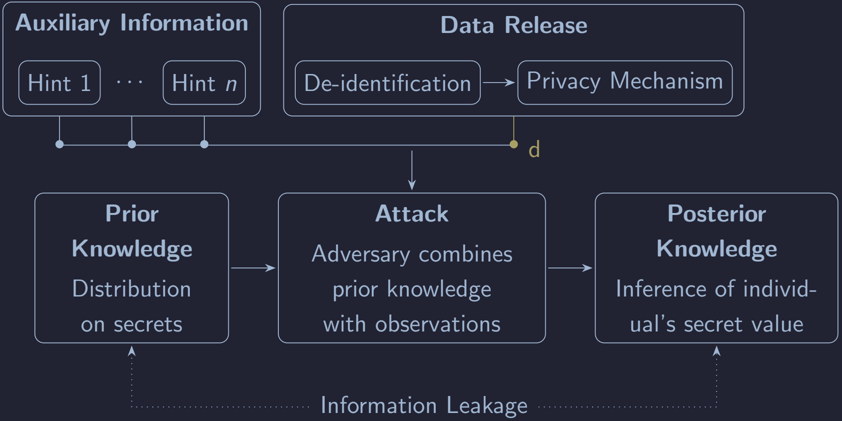
$$\begin{array}{c|c|} \pi & \\ x_1 & \frac{1}{|\mathcal{X}|} \\ x_2 & \frac{1}{|\mathcal{X}|} \\ x_3 & \frac{1}{|\mathcal{X}|} \\ x_4 & \frac{1}{|\mathcal{X}|} \\ x_5 & \frac{1}{|\mathcal{X}|} \\ \vdots & \vdots \end{array} \; [\triangleright] \; \begin{array}{c|ccc|} \mathrm{C}^{\text{Lineu}} & \langle \text{Pastry}, \text{Araujo}, d \rangle & \langle \text{Clinic}, \text{Araujo}, d \rangle & \cdots \\ x_1 & \frac{1}{2} & \frac{1}{2} & \cdots \\ x_2 & 0 & 0 & \cdots \\ x_3 & 0 & \frac{1}{6} & \cdots \\ x_4 & 0 & 0 & \cdots \\ x_5 & 0 & 0 & \cdots \\ \vdots & \vdots & \vdots & \vdots \end{array} = \begin{array}{c|ccc|} & \frac{4!}{2|\mathcal{X}|} \langle \text{Pastry}, \text{Araujo}, d \rangle & \frac{2 \cdot 4!}{3|\mathcal{X}|} \langle \text{Clinic}, \text{Araujo}, d \rangle & \cdots \\ x_1 & \frac{1}{4!} & \frac{3}{4 \cdot 4!} & \cdots \\ x_2 & 0 & 0 & \cdots \\ x_3 & 0 & \frac{1}{4 \cdot 4!} & \cdots \\ x_4 & 0 & 0 & \cdots \\ x_5 & 0 & 0 & \cdots \\ \vdots & \vdots & \vdots & \vdots \end{array}$$

There are 4! datasets similar to x_1, in which Lineu's record is $\vec{t}_1$, so

$$\left(\pi \triangleright \mathrm{C}^{\text{Lineu}}\right)_{\langle \text{Pastry}, \text{Araujo}, d \rangle} = {}^{4!}/(2|\mathcal{X}|)$$

Formal Model — Simplified Model — Fixed Dataset

We cannot compute over all possible de-identified datasets that could be released, so we focus on one particular dataset d, assuming the adversary has already observed it:



Auxiliary Information

Hint 1 · · · Hint n

Data Release

De-identification → Privacy Mechanism

d

Prior Knowledge

Distribution on secrets

Attack

Adversary combines prior knowledge with observations

Posterior Knowledge

Inference of individual's secret value

Information Leakage

Formal Model — Simplified Model — Fixed Dataset

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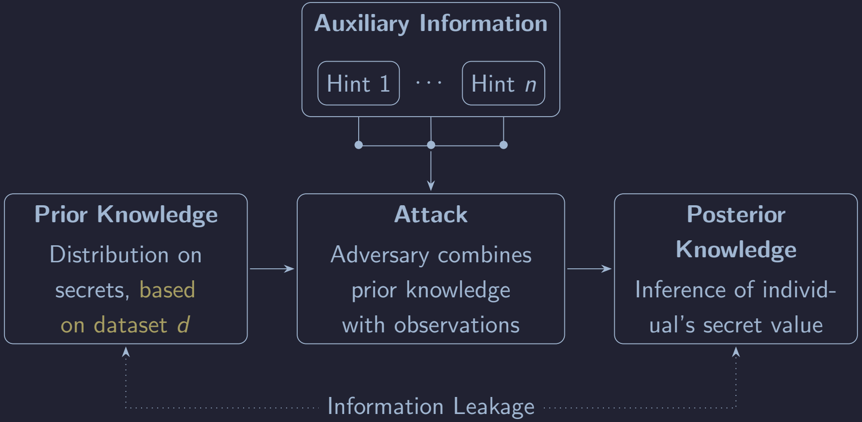

Auxiliary Information

Hint 1 $\cdots$ Hint n

Prior Knowledge

Distribution on secrets, based on dataset d

Attack

Adversary combines prior knowledge with observations

Posterior Knowledge

Inference of individual's secret value

Information Leakage

Formal Model — Simplified Model — Secrets

In our experiments, there are no two customers with the same transaction history. So, we can group secrets that are "similar". For instance, every dataset that maps to d in which Lineu's record is $\vec{t}_1$. Then, the space of secrets becomes the transaction histories:

$$
\begin{array}{cc}
 & \upsilon \\
\vec{t}_1 & \frac{1}{5} \\
\vec{t}_2 & \frac{1}{5} \\
\vec{t}_3 & \frac{1}{5} \\
\vec{t}_4 & \frac{1}{5} \\
\vec{t}_5 & \frac{1}{5}
\end{array}
\;[\triangleright]\;
\begin{array}{cccc}
\mathsf{C}^{\text{Lineu}} & \langle\text{Pastry, Araujo}\rangle & \langle\text{Clinic, Araujo}\rangle & \cdots \\
\vec{t}_1 & \frac{1}{2} & \frac{1}{2} & \cdots \\
\vec{t}_2 & 0 & 0 & \cdots \\
\vec{t}_3 & 0 & \frac{1}{6} & \cdots \\
\vec{t}_4 & 0 & 0 & \cdots \\
\vec{t}_5 & 0 & 0 & \cdots
\end{array}
=
\begin{array}{cccc}
 & \frac{1}{10}\,\langle\text{Pastry, Araujo}\rangle & \frac{2}{15}\,\langle\text{Clinic, Araujo}\rangle & \cdots \\
\vec{t}_1 & 1 & \frac{3}{4} & \cdots \\
\vec{t}_2 & 0 & 0 & \cdots \\
\vec{t}_3 & 0 & \frac{1}{4} & \cdots \\
\vec{t}_4 & 0 & 0 & \cdots \\
\vec{t}_5 & 0 & 0 & \cdots
\end{array}
$$

Formal Model — Simplified Model — Secrets

In our experiments, there are no two customers with the same transaction history. So, we can group secrets that are “similar”. For instance, every dataset that maps to d in which Lineu’s record is $\vec{t}_1$. Then, the space of secrets becomes the transaction histories:

$$\begin{array}{c|c|} \upsilon & \\ \vec{t}_1 & \frac{1}{5} \\ \vec{t}_2 & \frac{1}{5} \\ \vec{t}_3 & \frac{1}{5} \\ \vec{t}_4 & \frac{1}{5} \\ \vec{t}_5 & \frac{1}{5} \end{array} \; [\triangleright] \; \begin{array}{c|ccc|} \mathrm{C}^{\mathsf{Lineu}} & \langle \text{Pastry, Araujo} \rangle & \langle \text{Clinic, Araujo} \rangle & \cdots \\ \vec{t}_1 & \frac{1}{2} & \frac{1}{2} & \cdots \\ \vec{t}_2 & 0 & 0 & \cdots \\ \vec{t}_3 & 0 & \frac{1}{6} & \cdots \\ \vec{t}_4 & 0 & 0 & \cdots \\ \vec{t}_5 & 0 & 0 & \cdots \end{array} = \begin{array}{c|ccc|} & \frac{1}{10}\,\langle \text{Pastry, Araujo} \rangle & \frac{2}{15}\,\langle \text{Clinic, Araujo} \rangle & \cdots \\ \vec{t}_1 & 1 & \frac{3}{4} & \cdots \\ \vec{t}_2 & 0 & 0 & \cdots \\ \vec{t}_3 & 0 & \frac{1}{4} & \cdots \\ \vec{t}_4 & 0 & 0 & \cdots \\ \vec{t}_5 & 0 & 0 & \cdots \end{array}$$

and the gain function $\mathbf{1}_{\mathsf{Lineu}}$ is replaced with $\mathbf{1}$

Formal Model — Simplified Model — Quantifying Leakage

$$\begin{array}{c|cccc|}
 & \frac{1}{10}\,\langle\text{Pastry, Araujo}\rangle & \frac{2}{15}\,\langle\text{Clinic, Araujo}\rangle & \frac{1}{30}\,\langle\text{Clinic, Pastry}\rangle & \cdots \\
\vec{t}_1 & 1 & \frac{3}{4} & 0 & \cdots \\
\vec{t}_2 & 0 & 0 & 0 & \cdots \\
\vec{t}_3 & 0 & \frac{1}{4} & 1 & \cdots \\
\vec{t}_4 & 0 & 0 & 0 & \cdots \\
\vec{t}_5 & 0 & 0 & 0 & \cdots
\end{array}$$

Formal Model — Simplified Model — Quantifying Leakage

$$\begin{array}{c|cccc} & \frac{1}{10}\,\langle\text{Pastry}, \text{Araujo}\rangle & \frac{2}{15}\,\langle\text{Clinic}, \text{Araujo}\rangle & \frac{1}{30}\,\langle\text{Clinic}, \text{Pastry}\rangle & \cdots \\ \hline \vec{t}_1 & 1 & \frac{3}{4} & 0 & \cdots \\ \vec{t}_2 & 0 & 0 & 0 & \cdots \\ \vec{t}_3 & 0 & \frac{1}{4} & 1 & \cdots \\ \vec{t}_4 & 0 & 0 & 0 & \cdots \\ \vec{t}_5 & 0 & 0 & 0 & \cdots \end{array}$$

- The prior vulnerability is then $V_{\mathbf{1}}(v) = {}^{1}/_{5}$

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\vec{t}_3 & 0 & \frac{1}{4} & 1 & \cdots \\
\vec{t}_4 & 0 & 0 & 0 & \cdots \\
\vec{t}_5 & 0 & 0 & 0 & \cdots
\end{array}$$

- The prior vulnerability is then $V_{\mathbf{1}}(\upsilon) = {}^{1}\!/_{5}$
- The posterior vulnerability is $V_{\mathbf{1}}[\upsilon \triangleright \mathsf{C}^{\mathsf{Lineu}}] = {}^{1}\!/_{10} + {}^{2}\!/_{15} \cdot {}^{3}\!/_{4} + {}^{1}\!/_{30} + \cdots = {}^{14}\!/_{15}$

$$\begin{array}{c|cccc} & \frac{1}{10}\,\langle \text{Pastry}, \text{Araujo}\rangle & \frac{2}{15}\,\langle \text{Clinic}, \text{Araujo}\rangle & \frac{1}{30}\,\langle \text{Clinic}, \text{Pastry}\rangle & \cdots \\ \vec{t}_1 & 1 & \frac{3}{4} & 0 & \cdots \\ \vec{t}_2 & 0 & 0 & 0 & \cdots \\ \vec{t}_3 & 0 & \frac{1}{4} & 1 & \cdots \\ \vec{t}_4 & 0 & 0 & 0 & \cdots \\ \vec{t}_5 & 0 & 0 & 0 & \cdots \end{array}$$

- The prior vulnerability is then $V_{\mathbf{1}}(\upsilon) = {}^1\!/_5$
- The posterior vulnerability is $V_{\mathbf{1}}[\upsilon \triangleright \mathsf{C}^{\mathsf{Lineu}}] = {}^1\!/_{10} + {}^2\!/_{15} \cdot {}^3\!/_4 + {}^1\!/_{30} + \cdots = {}^{14}\!/_{15}$
- The information that leaks in this attack is thus $\mathcal{L}_{\mathbf{1}}(\upsilon, \mathsf{C}^{\mathsf{Lineu}}) = {}^{14}\!/_3 \approx 4.67$

Conclusion & Future Work

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- This project has recently resulted in a grant from the Australian Research Council (ARC), under the 2025 Discovery Projects program!