38º Brazilian Symposium on Databases
V Database Thesis and Dissertation Competition

Towards Auditable and Intelligent Privacy-Preserving Record Linkage

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PPGCC/UFCG (2018 - 2022)

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AGENDA

I. Introduction
II. PPRL Comparison step Auditability
III. Unsupervised Classification step for PPRL
IV. Deep Learning-based Classifiers for PPRL
V. Final Arguments

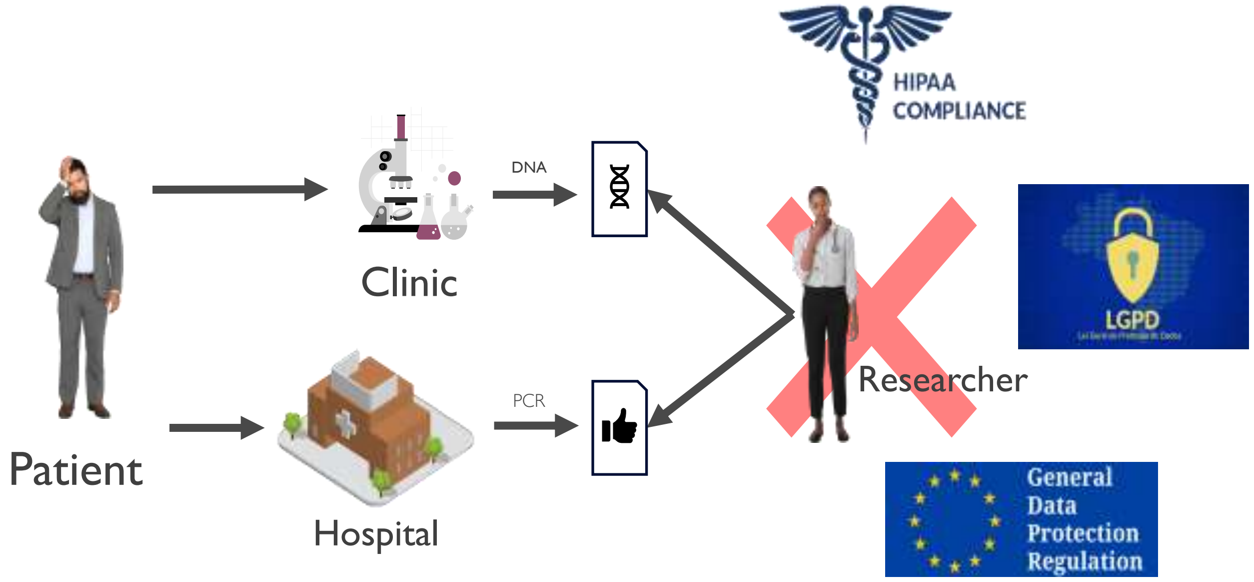
Introduction

Motivation

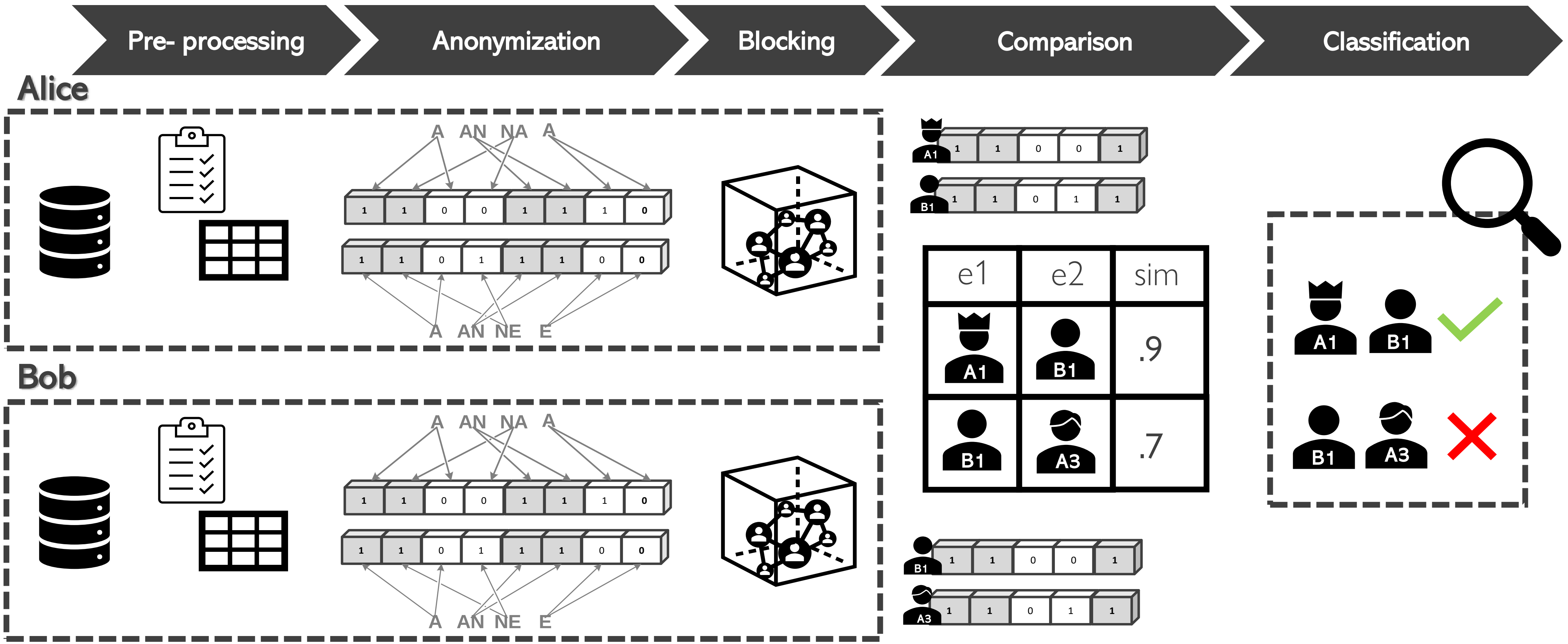
PPRL Goal

“The goal of PPRL is to perform record linkage without revealing entities identifiers”.

- ❑ Absence of unique identifiers



PPRL Process



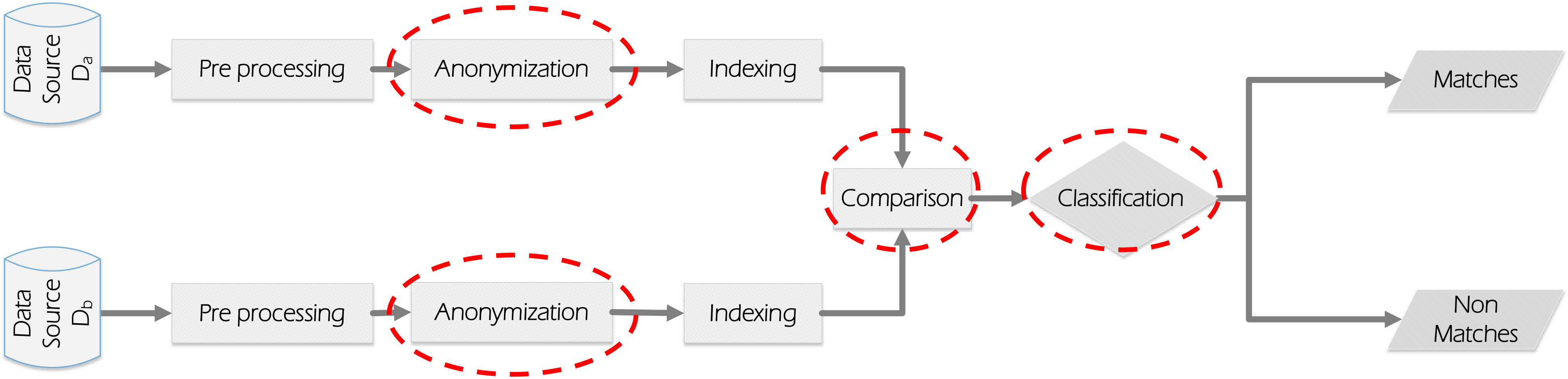
PPRL Limitations

Privacy

- Adversary Model

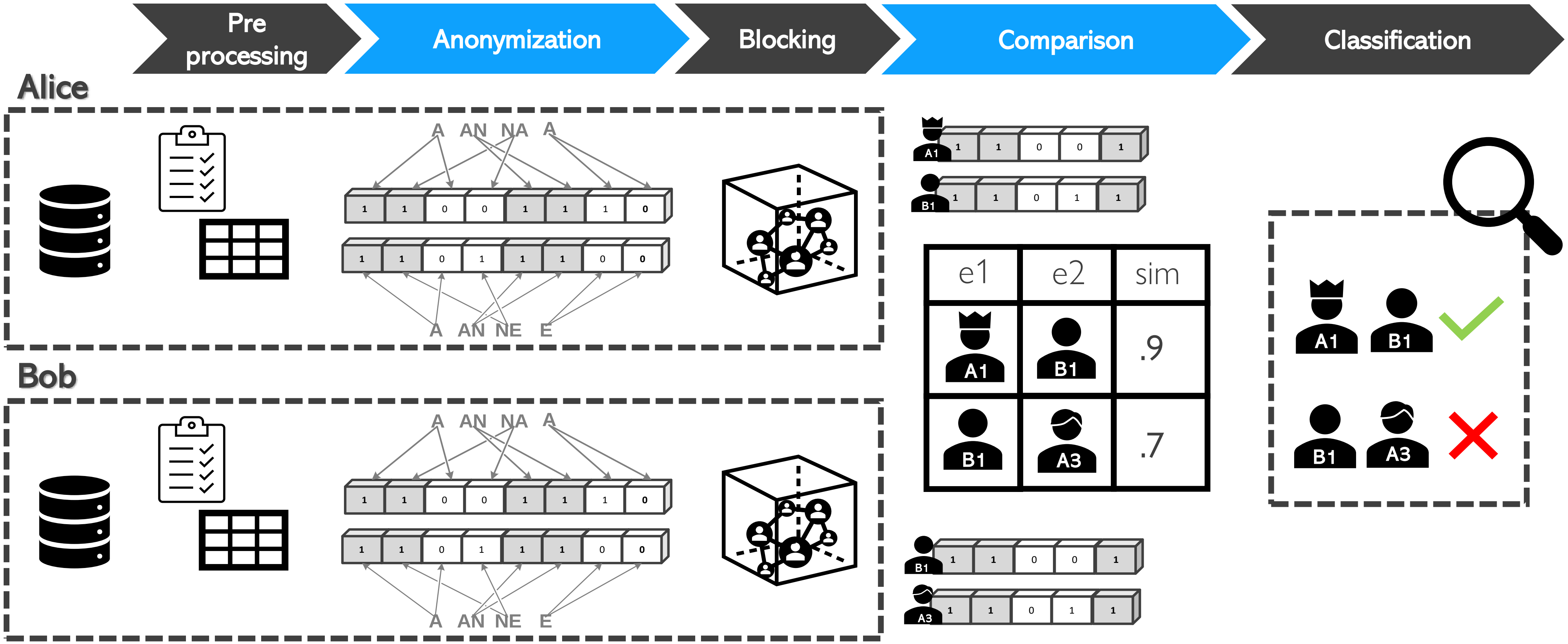
Quality

- Low Linkage Quality

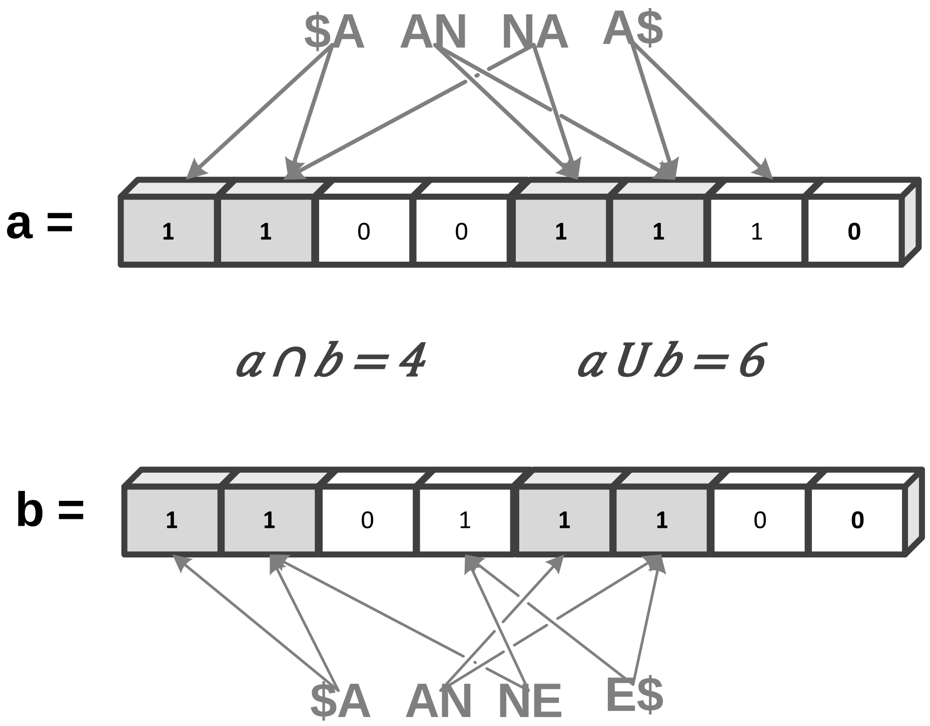


PPRL Comparison step Auditability

PPRL Comparison step Limitations



PPRL Anonimization

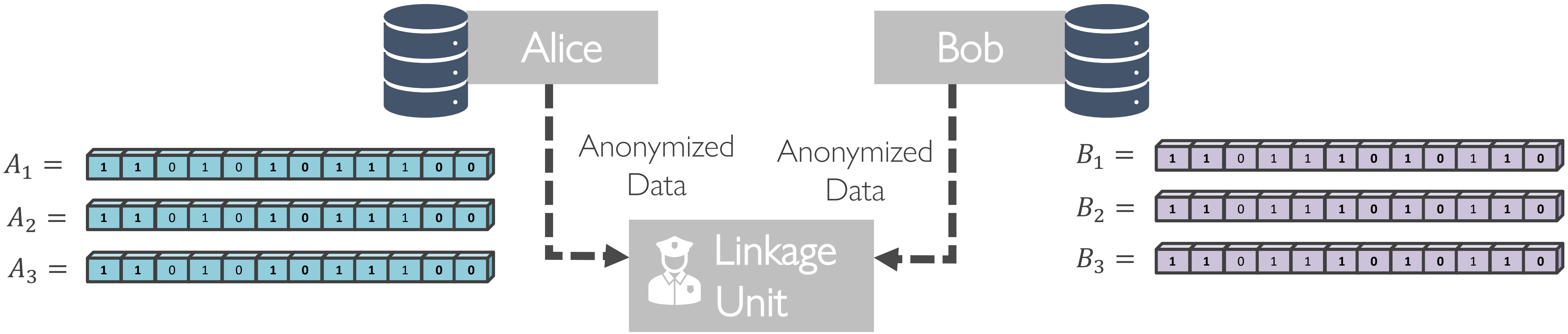


$a \cap b = 4$ $\quad$ $a \, U \, b = 6$

$$Dice(a,b) = \frac{2 \times |a \cap b|}{|a| + |b|} \rightarrow \frac{8}{10} \rightarrow 0.8$$

$$Jaccard(a,b) = \frac{|a \cap b|}{|a \, U b|} \rightarrow \frac{4}{6} \rightarrow 0.65$$

PPRL Comparison step Limitations



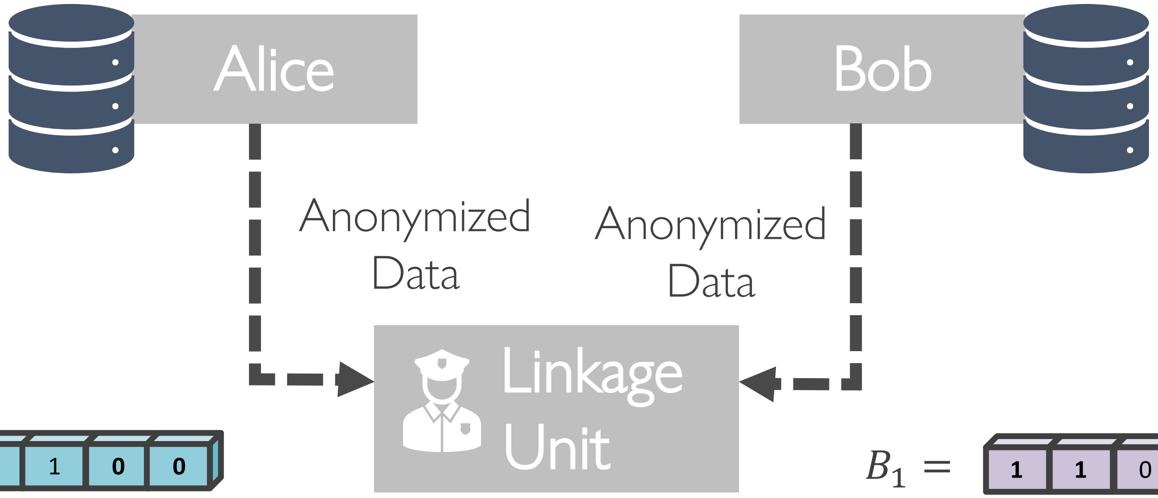
i. Shared Information

ii. Need to fully trust other PPRL parties

SBF

Splitting Bloom Filter

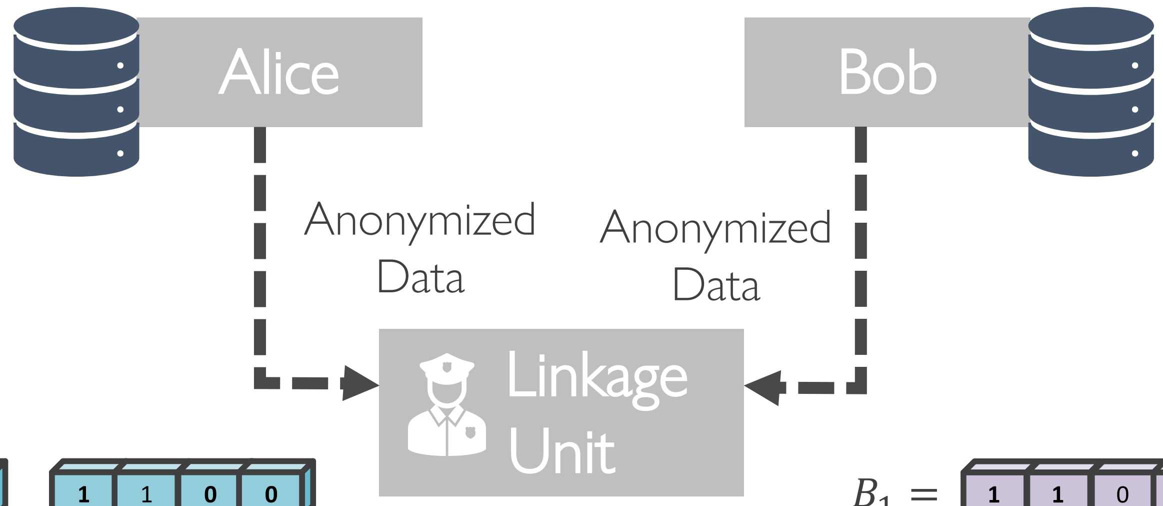
SBF



$A_1 = [1\ 1\ 0\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 0\ 0]$

$B_1 = [1\ 1\ 0\ 1\ 1\ 1\ 0\ 1\ 0\ 1\ 1\ 0]$

SBF

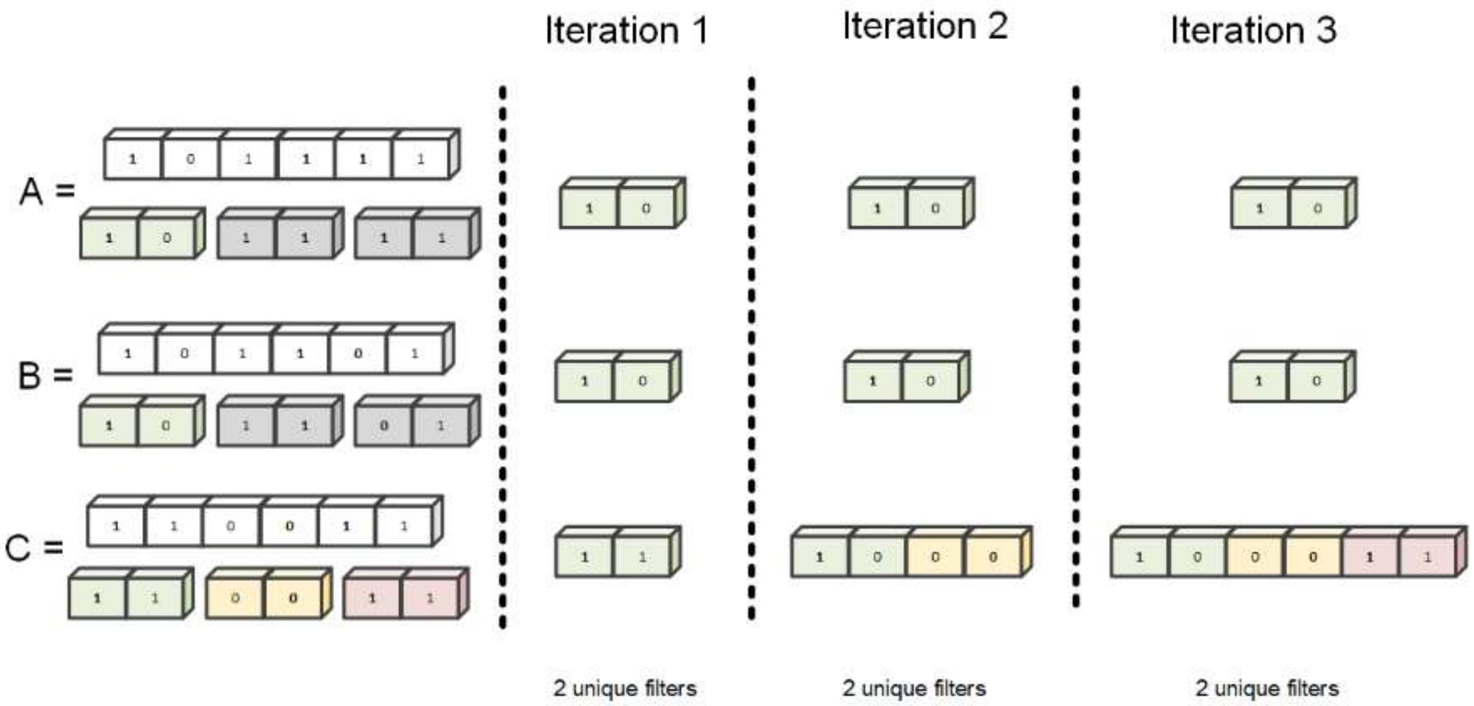


$A_1 = [1\ 1\ 0\ 1], [0\ 1\ 0\ 1], [1\ 1\ 0\ 0]$

$B_1 = [1\ 1\ 0\ 1], [1\ 1\ 0\ 1], [0\ 1\ 1\ 0]$

SBF

Privacy Motivation



- Indistinguishability
- Uncertainty
- Split FIltering

“What is the impact of utilizing partial fragments (splits) of the original Bloom Filter on data comparisons?”

SBF

Shared Information

ANA ANE

$$Jaccard(110101011100,\ 110111010110) = Jaccard(1101,\ 1101) + \boldsymbol{error}$$

$$\boldsymbol{error} = \binom{\frac{l}{s}}{x} p^{x}(1-p)^{\frac{l}{s}-x}$$

SBF

Requirement

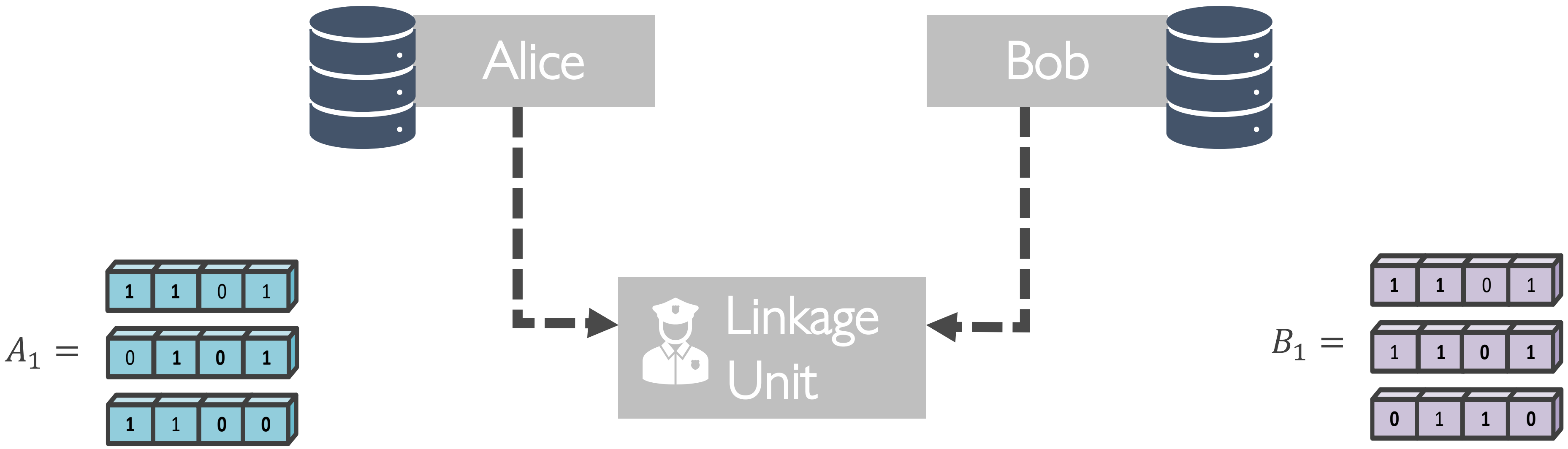
$$Jaccard\Big(\underset{\text{ANA}}{\overset{\text{ANA}}{[1\,1\,0\,1\,0\,1\,0\,1\,1\,1\,0\,0]}},\ \overset{\text{ANE}}{[1\,1\,0\,1\,1\,1\,0\,1\,0\,1\,1\,0]}\Big) \cong \frac{1}{s}\sum_{1}^{s} Jaccard\left(\phi_A^i, \phi_B^i\right)$$

$$\phi_A = \begin{matrix} [1\,1\,0\,1] \\ [0\,1\,0\,1] \\ [1\,1\,0\,0] \end{matrix} \qquad \phi_B = \begin{matrix} [1\,1\,0\,1] \\ [1\,1\,0\,1] \\ [0\,1\,1\,0] \end{matrix}$$

ABEL

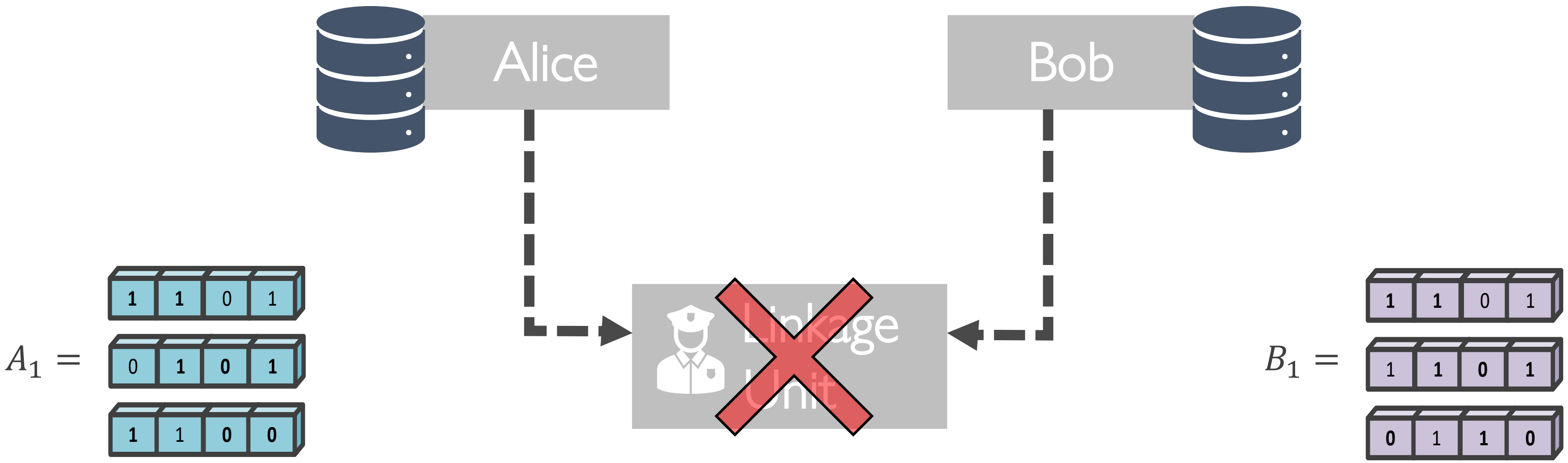
Auditable Blockchain-based PPRL

PPRL Comparison step Limitations



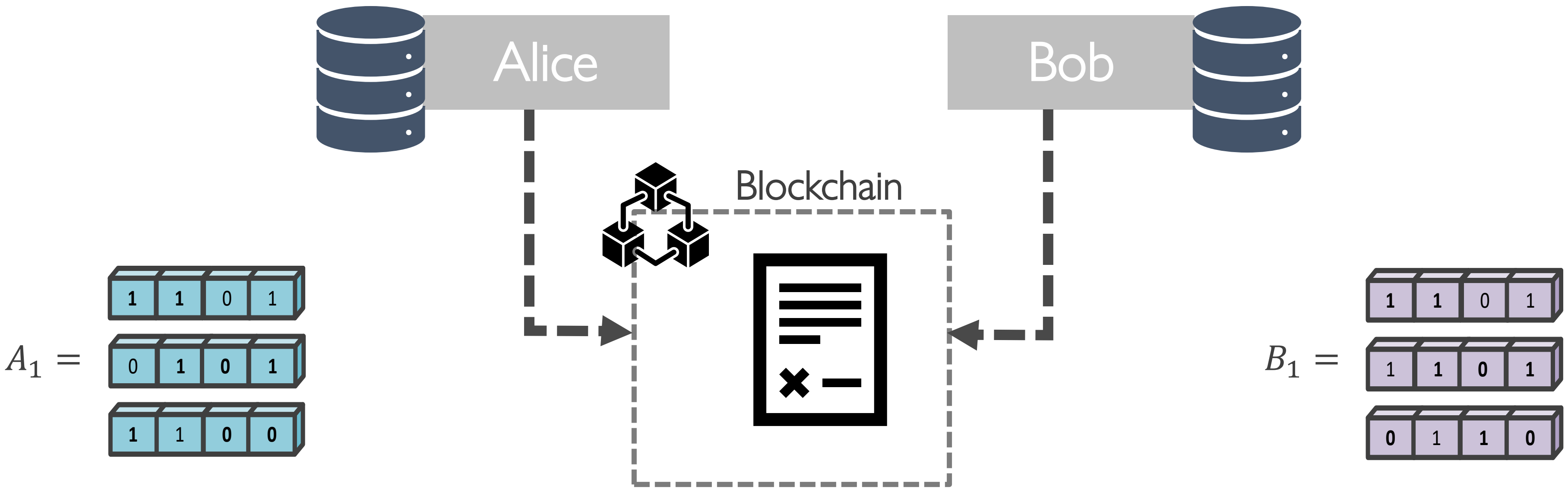
ABEL

Auditability



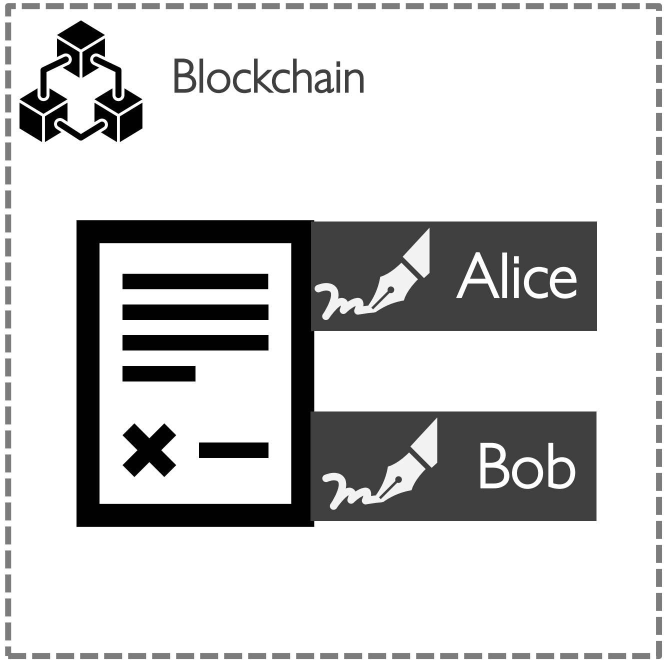
ABEL

Auditability

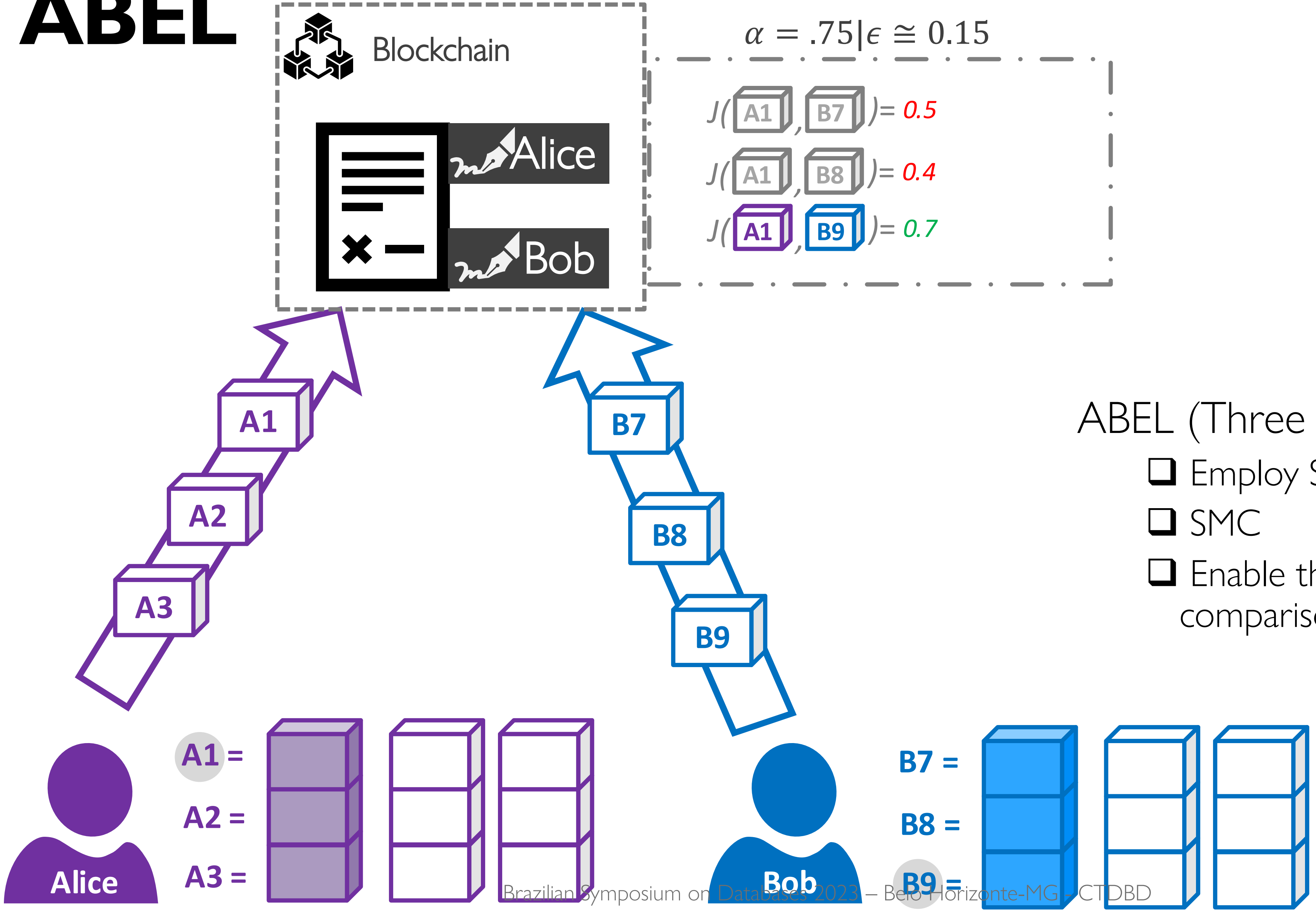


ABEL

Auditability



ABEL



ABEL (Three Party Protocol)

- ❑ Employ SBC error (ϵ)
- ❑ SMC
- ❑ Enable the auditability of PPRL comparison step

EVALUATION

SBF & ABEL Linkage Quality and Privacy

Evaluation Metrics

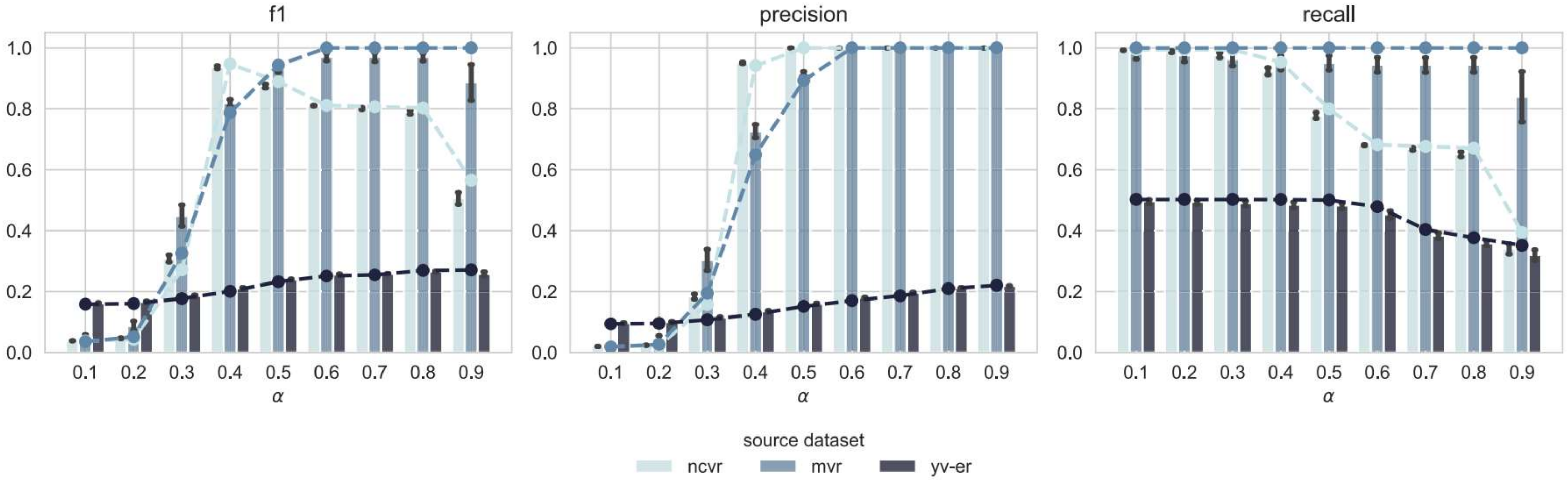
Linkage Quality

- Compare ABEL against the standard comparation step
  - precision
  - recall
  - F1

Privacy

- Measure ABEL privacy cost
  - Reidentification rate against a customized attack

Overall quality results



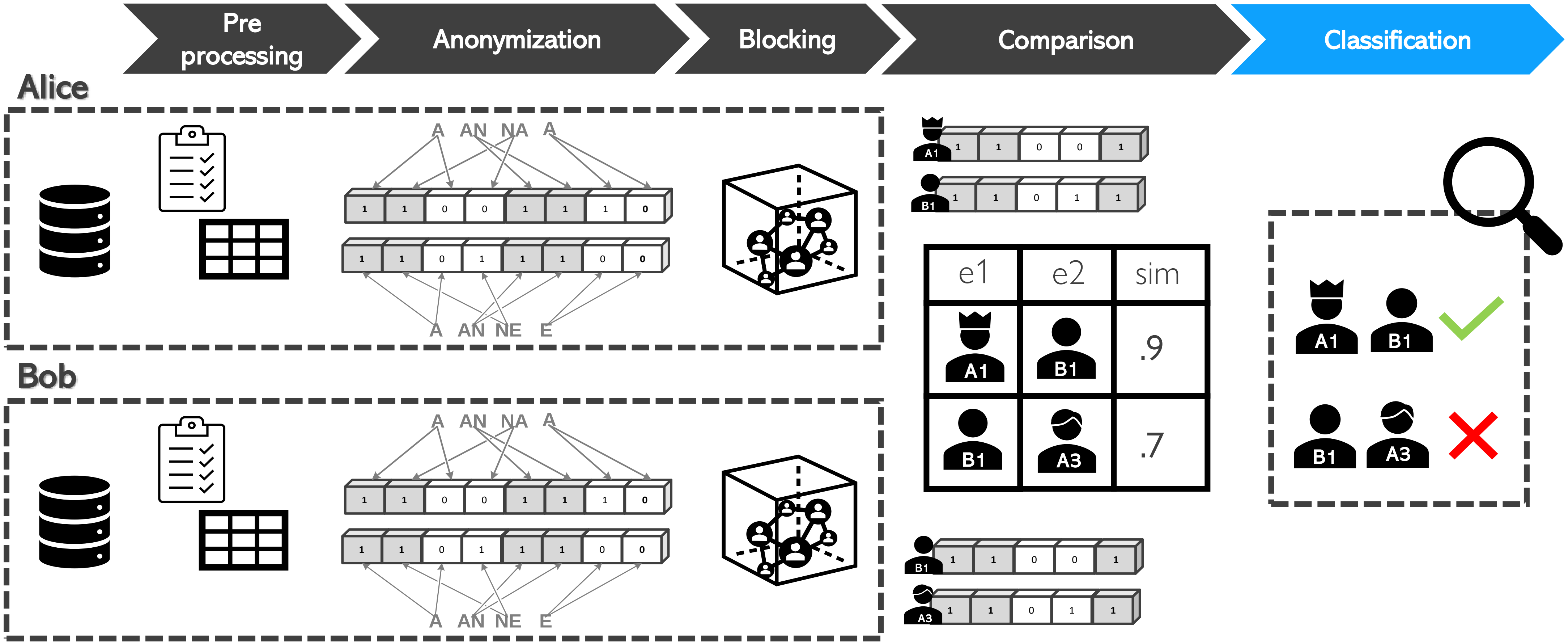
Privacy

Attack Effectiveness Comparison

Publication	Dataset	Num BF	1-to-1 correct	1-to-1 correct %
Pattern-mining based for PPRL [30]	NCVR diff. attr.	>200k	>49k	25%
Precise and Fast Cryptanalysis for PPRL [26]	NCVR First + Last name	>200k	-	20.7%
A Graph Matching Attack [169]	NCVR First + Last name	100k	-	>50% accuracy >90% accuracy
this work	NCVR First + Last name	10k	1,346	13%

Unsupervised Classification step for PPRL

Limitations of PPRL Classification step



Limitations of PPRL Classification Step

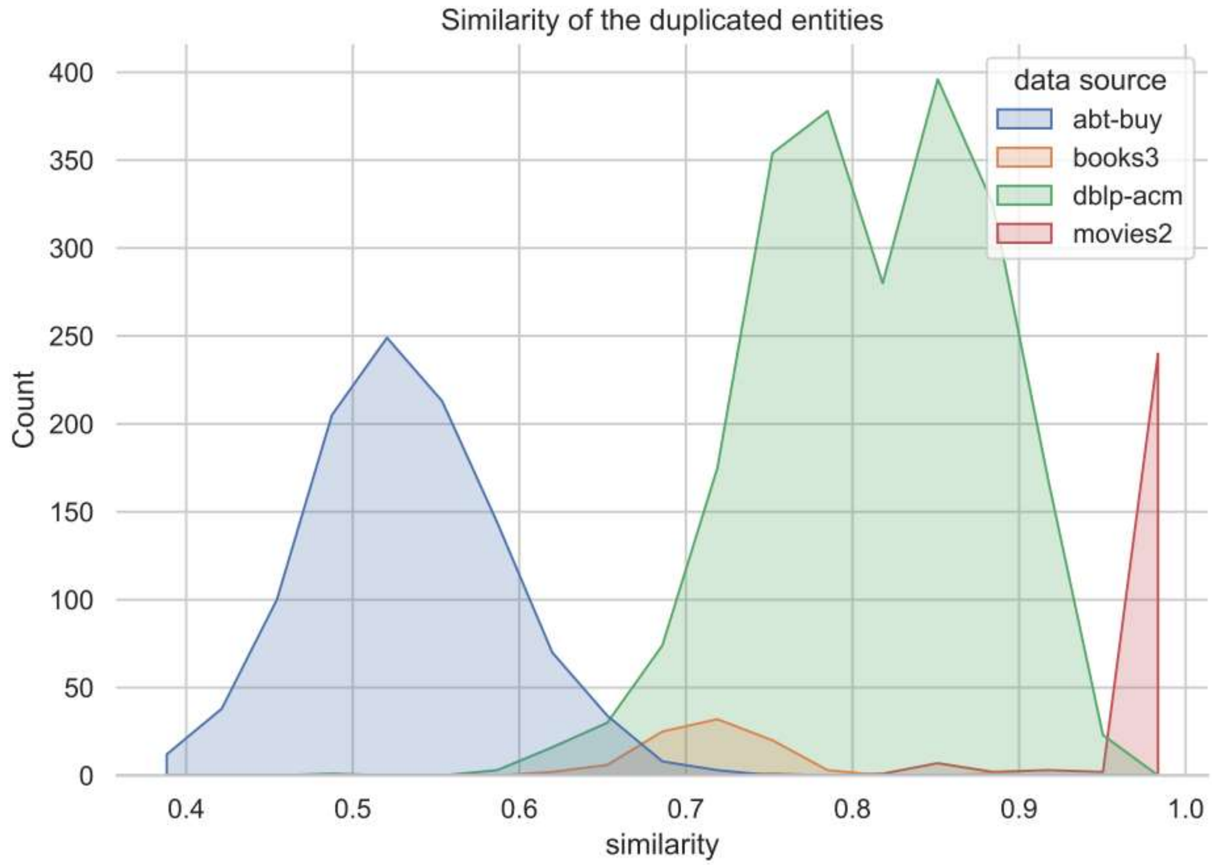
e1	e2	sim
A1	B1	.9
B1	A3	.8

Threshold

- Hard to tune

Automatic (Machine Learning based)

- Privacy Limitations
- No labeled data
- No oracle available
- No access to actual data

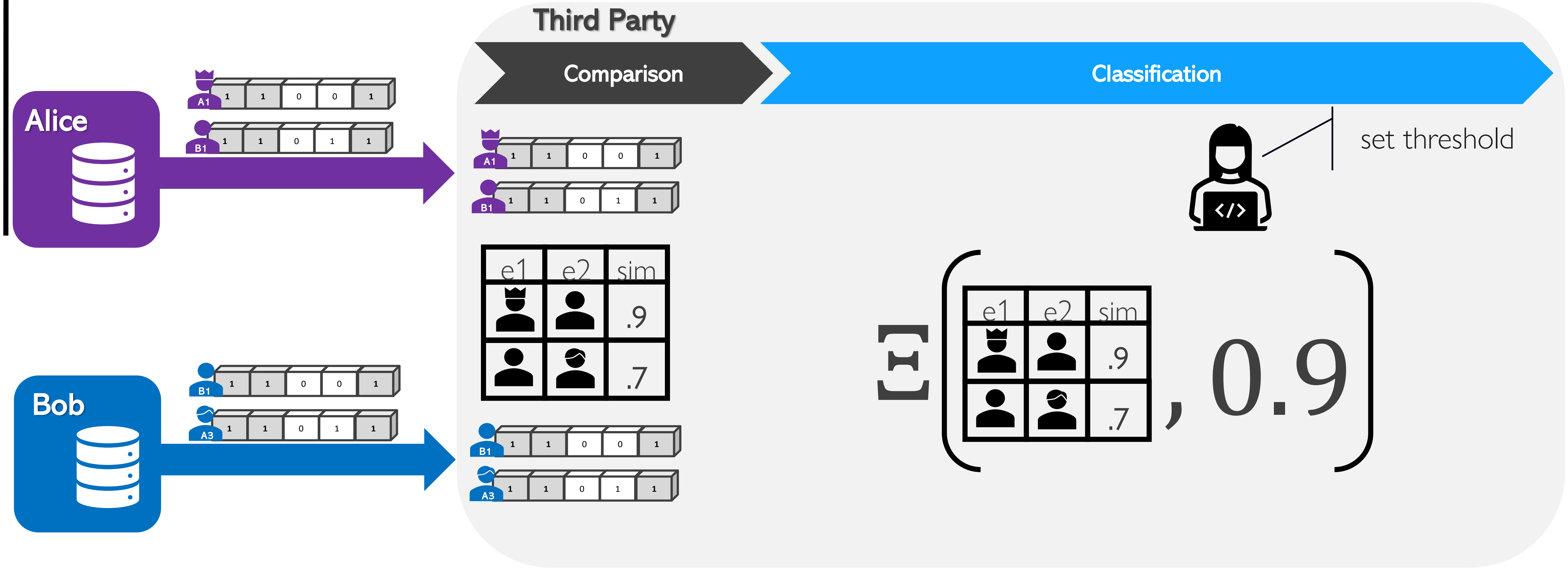


AT-UC

Auto-Tuned Unsupervised Classification

AT-UC

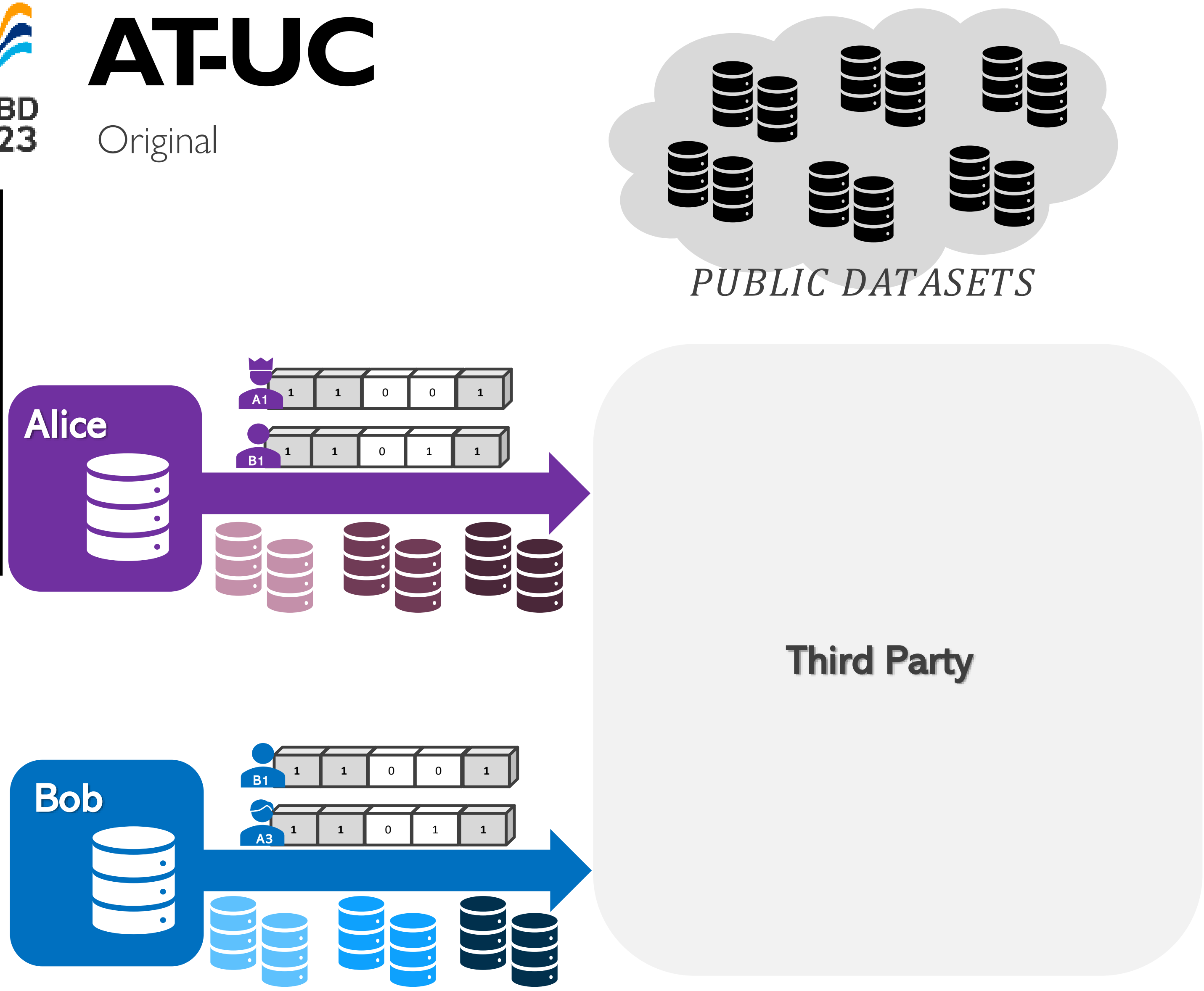
Original



$$\Xi(S,\lambda) = \{x \in S \mid x \geq \lambda\}$$

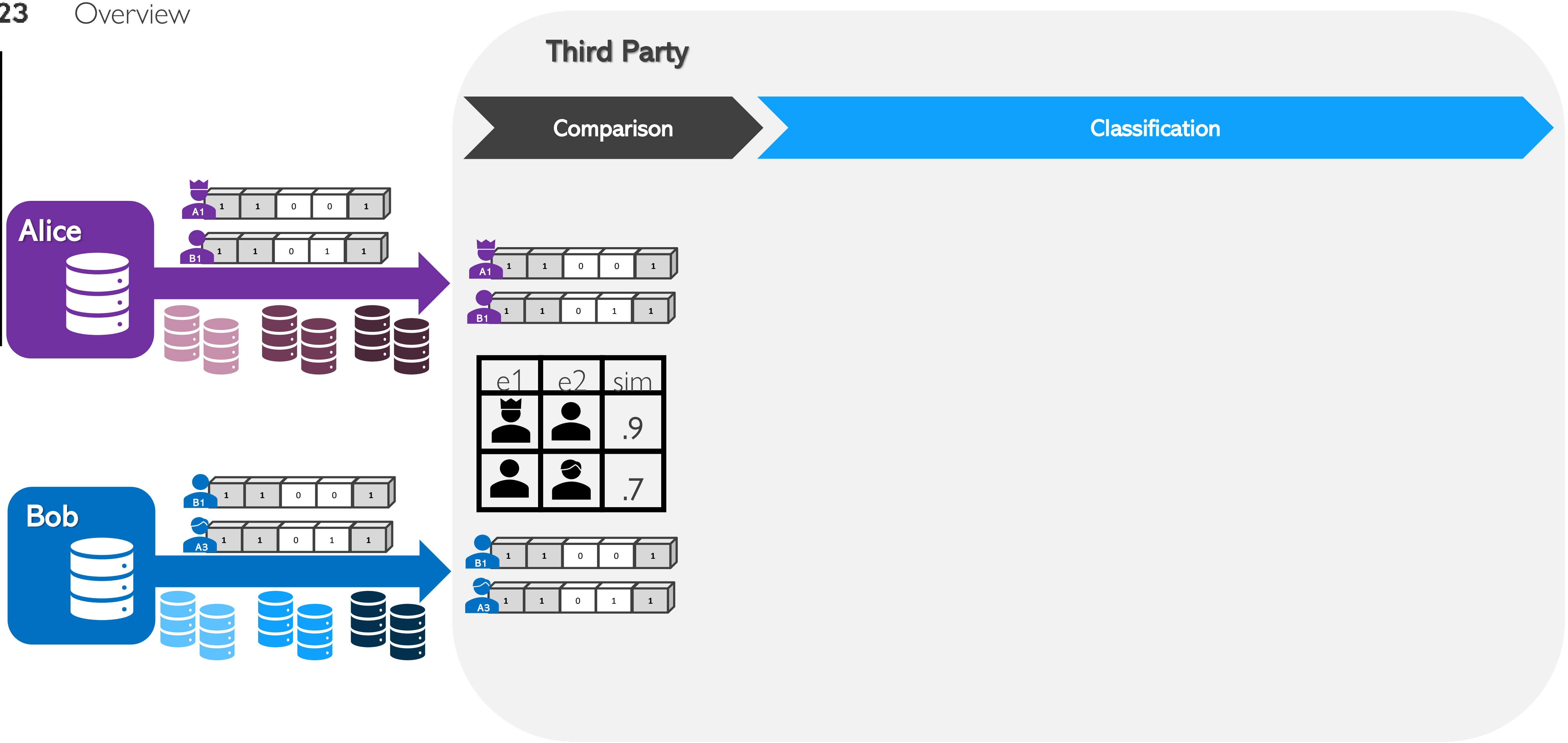
AT-UC

Original



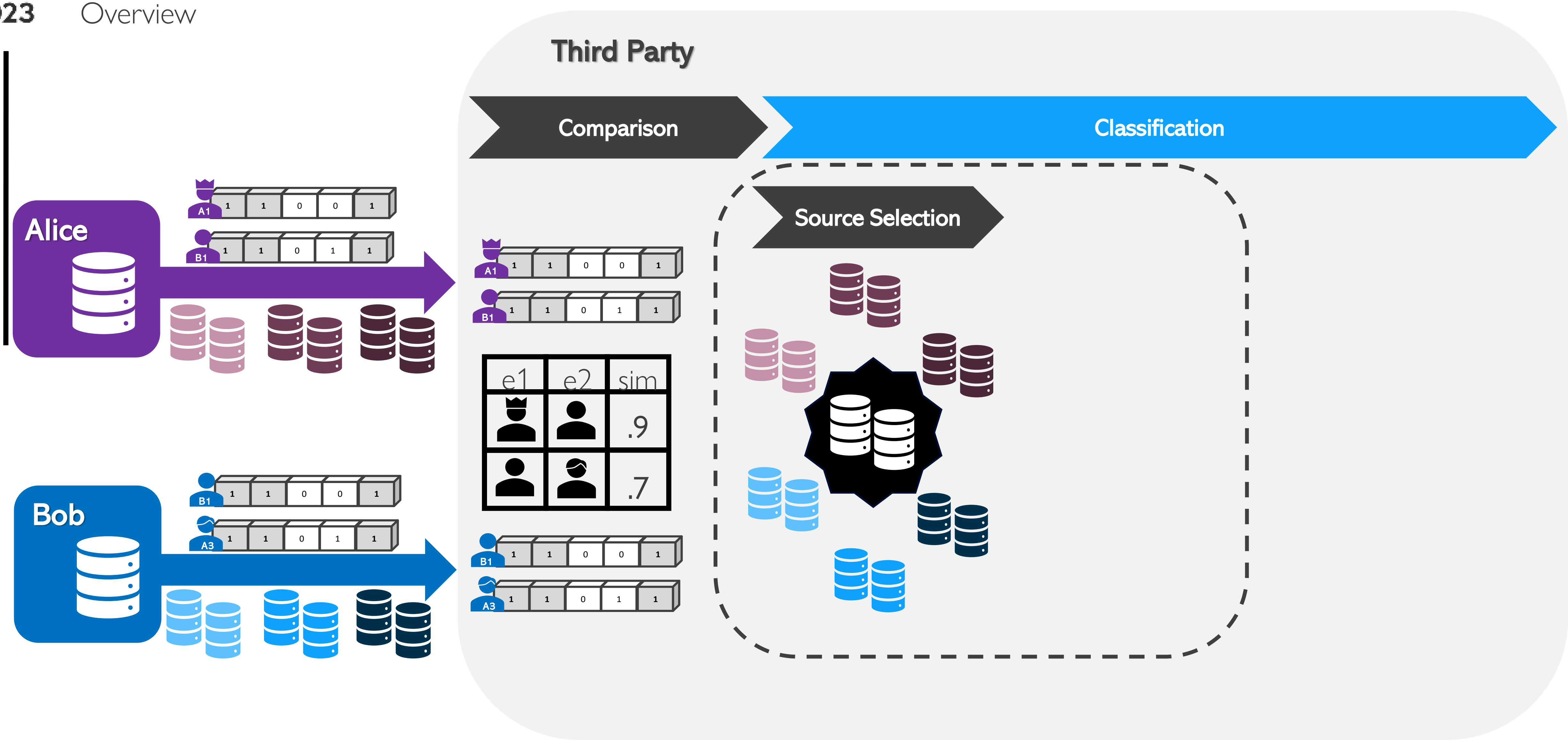
AT-UC

Overview



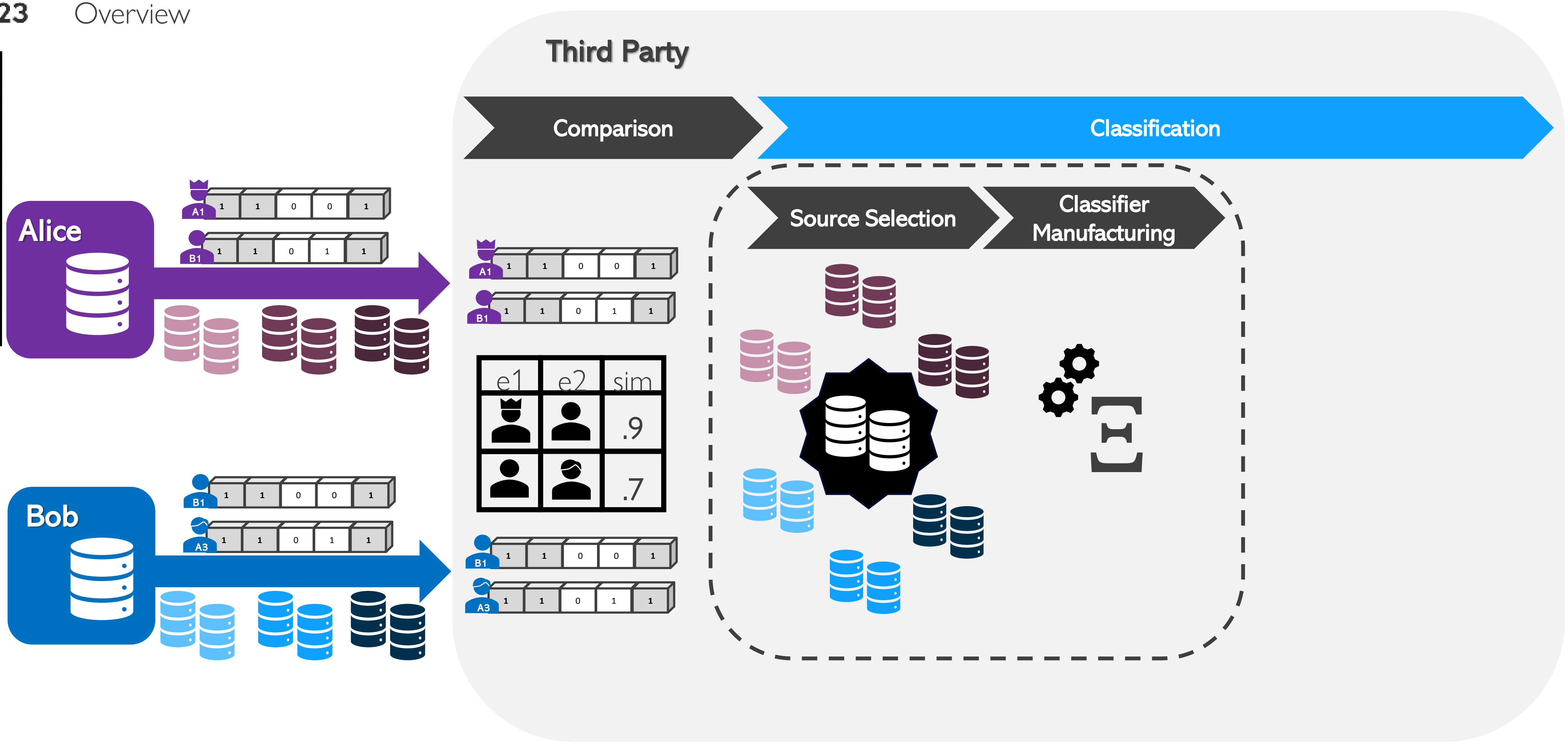
AT-UC

Overview



AT-UC

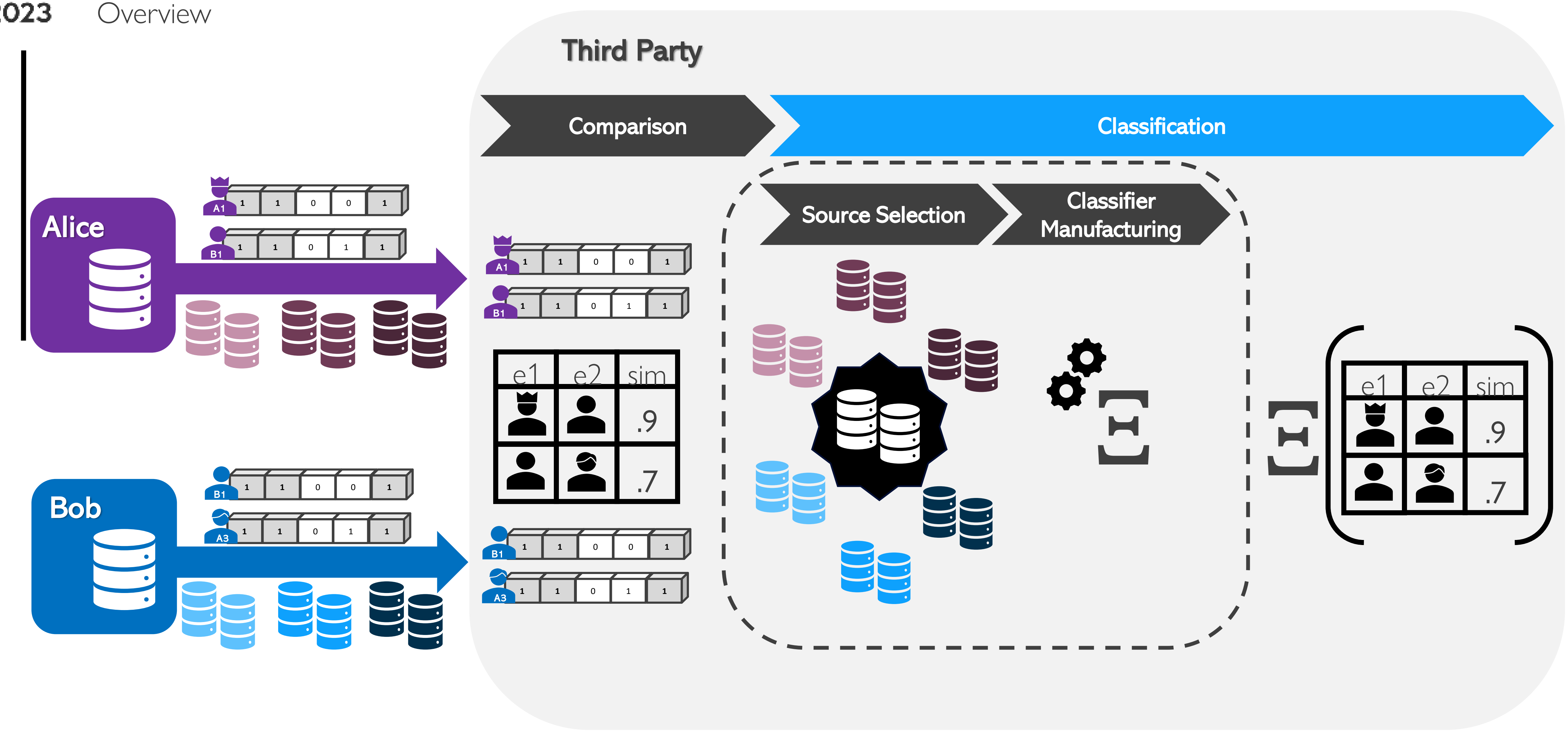
Overview



AT-UC

SBBD 2023

Overview



EVALUATION

AT-UC Linkage Quality, Efficiency and Privacy

Evaluation Metrics

Linkage Quality

- Measure Source Selection stage impact
  - F1
- Compare AT-UC against a baseline and competitors
  - precision, recall, F1

Privacy

- Measure AT-UC privacy cost
  - Reidentification rate against an attack

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Linkage Quality

Linkage Quality Comparison

Baseline

- threshold

Competitors

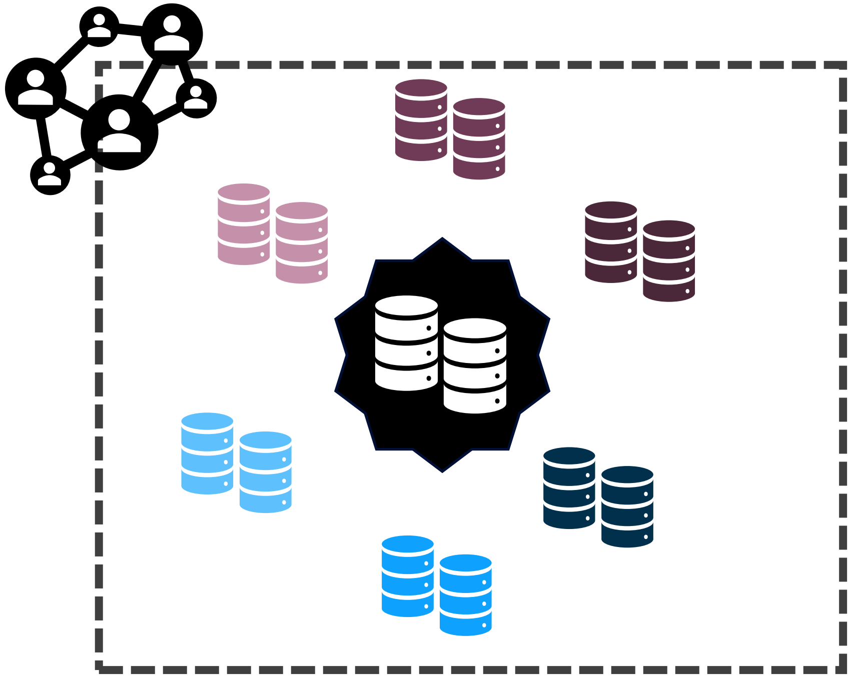
- transER
- coral
- naive

approach	target	source	precision	recall	f1
at-uc	census	restaurants	14%	77%	**22%**
	mvr	census	97%	99%	**98%**
	ncvr	census	100%	78%	**87%**
	tse	books	84%	87%	**85%**
	yv-er	tse	66%	56%	**61%**
naive	census	best	1%	100%	2%
	mvr	best	5%	99%	9%
	ncvr	best	2%	91%	4%
	tse	best	0%	13%	0%
	yv-er	best	43%	87%	58%
transER	census	-	-	-	-
	mvr	best	83%	99%	90%
	ncvr	best	74%	99%	85%
	tse	best	3%	100%	6%
	yv-er	-	-	-	-
coral	census	5-best	9% ±6%	49% ±6%	15% ±9%
	mvr	5-best	96% ±1%	88% ±1%	91% ±8%
	ncvr	5-best	99%	49%	66%
	tse	5-best	81% ±1%	80% ±1%	80% ±8%
	yv-er	5-best	93% ±15%	40% ±15%	46% ±45%
threshold	census	5-best	8% ±5%	61% ±5%	14% ±9%
	mvr	5-best	49% ±46%	71% ±46%	51% ±44%
	ncvr	5-best	49% ±47%	67% ±47%	49% ±42%
	tse	5-best	27% ±24%	71% ±34%	32% ±31%
	yv-er	5-best	60% ±42%	64% ±42%	60% ±39%

Privacy

Experimental Setup

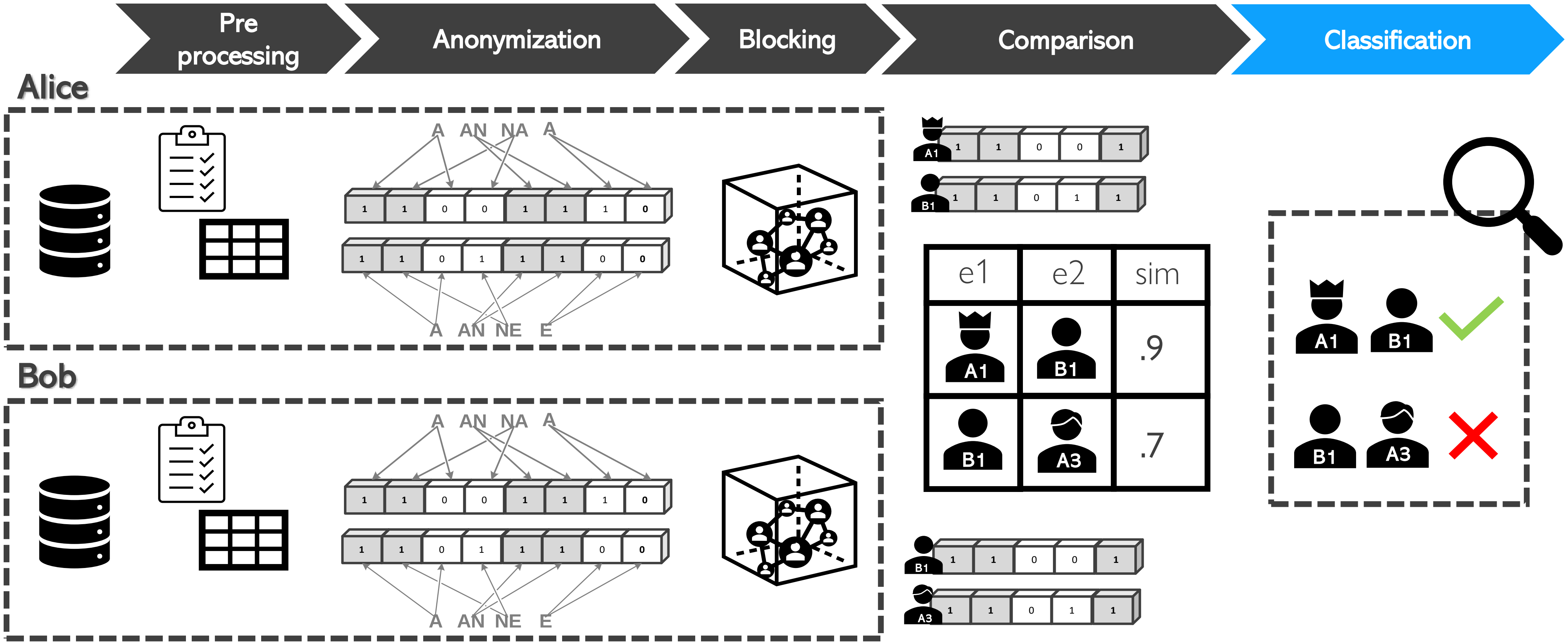
- A Graph Matching Attack (Radanbuge et. al, 2020)



Scenario	Accuracy
Original Attack Result	90%
AT-UC Scenario	0%

Deep Learning-based Classifiers for PPRL

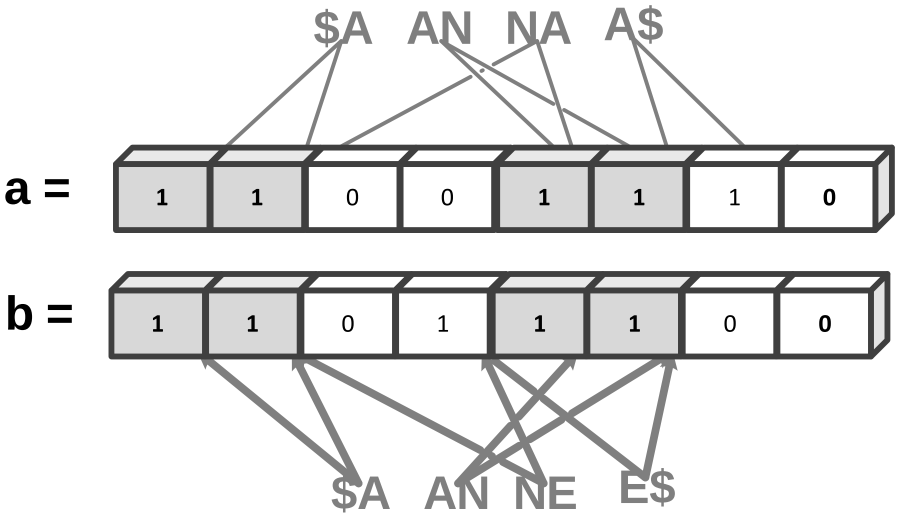
Limitations of PPRL Classification step



Limitations of PPRL Classification step

Similarity measures bias

- Encoding Limitation
- Similarity measures limitation



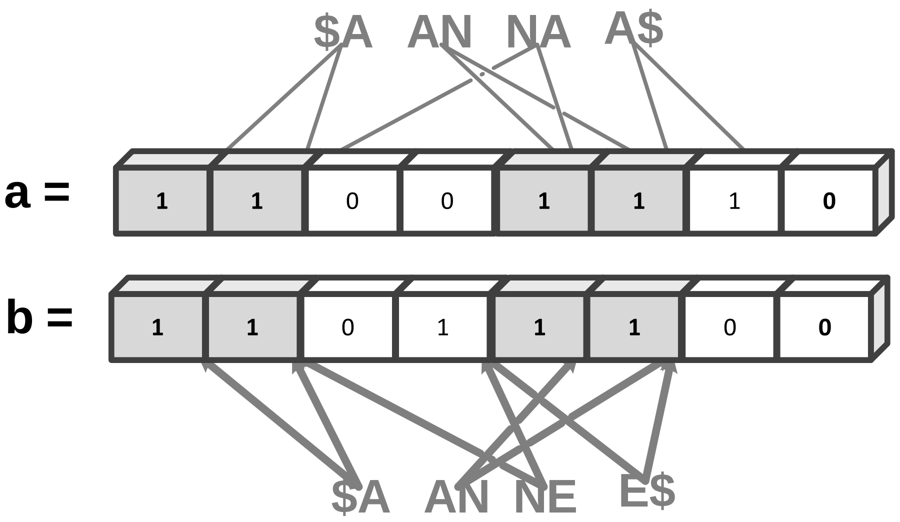
DICE(a,b)=.66

DLC

Deep Learning-based Classifier for PPRL

DLC

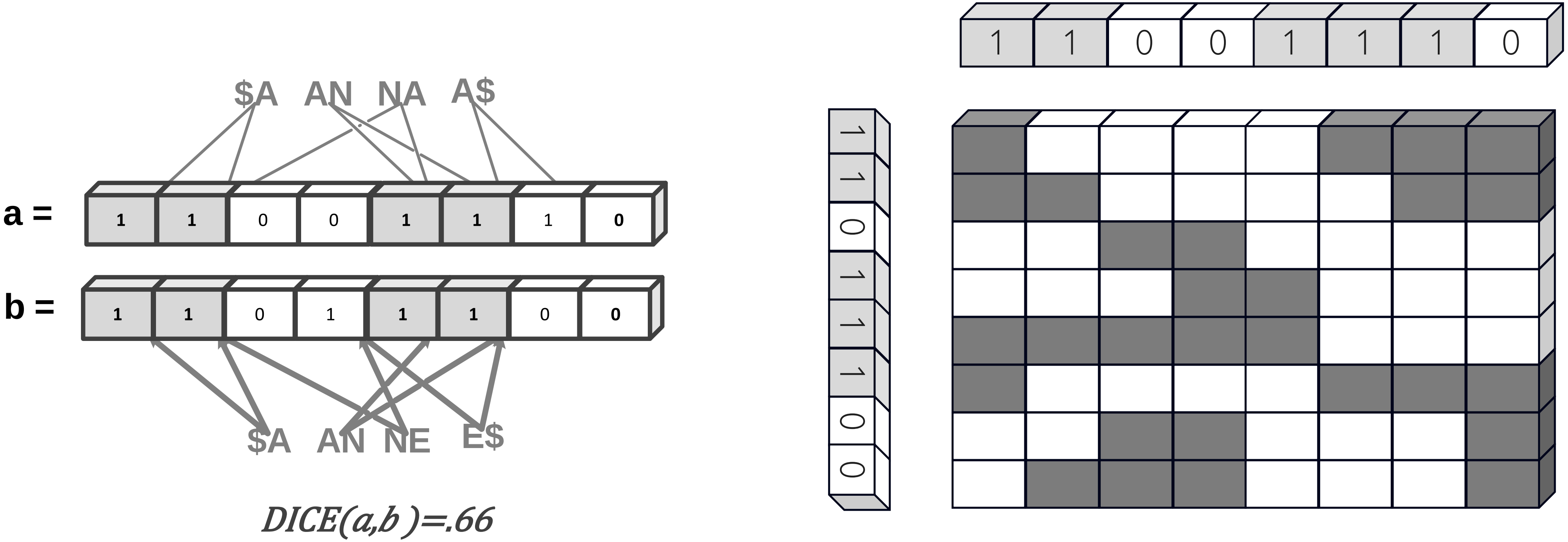
How to extract the BF patterns?



DICE(a,b)=.66

DLC

How to extract the BF patterns?



DLC

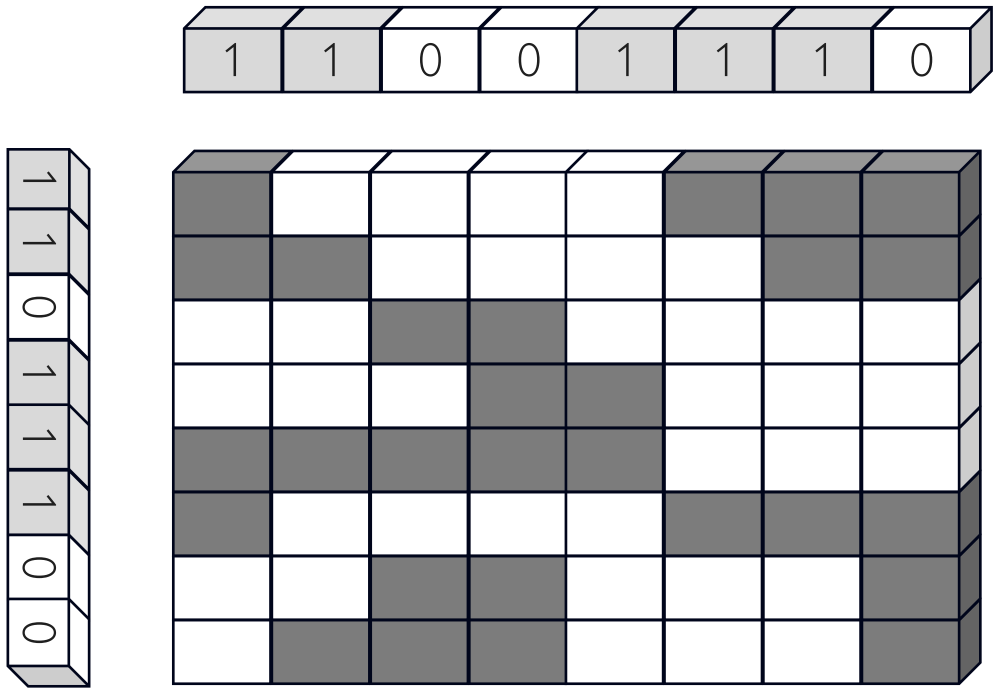
Recurrence Plot as a Feature Space

CRP highlights common states (e.g., bits) over encoded record pairs

- CRP Parameters
  i. Encoded Record $(\hat{\mathbf{e}}_1, \hat{\mathbf{e}}_2)$
     - l = number of bits $\hat{\mathbf{e}}_1$ and $\hat{\mathbf{e}}_2$
  ii. Neighbors (m)
  iii. Heaviside Threshold (α)
- $CRP(\hat{\mathbf{e}}_1, \hat{\mathbf{e}}_2, m, \alpha) = RP_{n \times n}$, such as $n = l - (m-1)$

$$CRP(\hat{\mathbf{e}}_1, \hat{\mathbf{e}}_2, m, \alpha) = \sum_{i=0}^{l} \sum_{j=0}^{l} \Theta\left(\alpha, \sum_{w=0}^{m} ||\hat{\mathbf{e}}_1[i+w] - \hat{\mathbf{e}}_2[i+w]||\right)$$

$$\Theta(\alpha_i, v) = \begin{cases} 1 : & v \leq \alpha_i \\ 0 : & v > \alpha_i \end{cases}$$

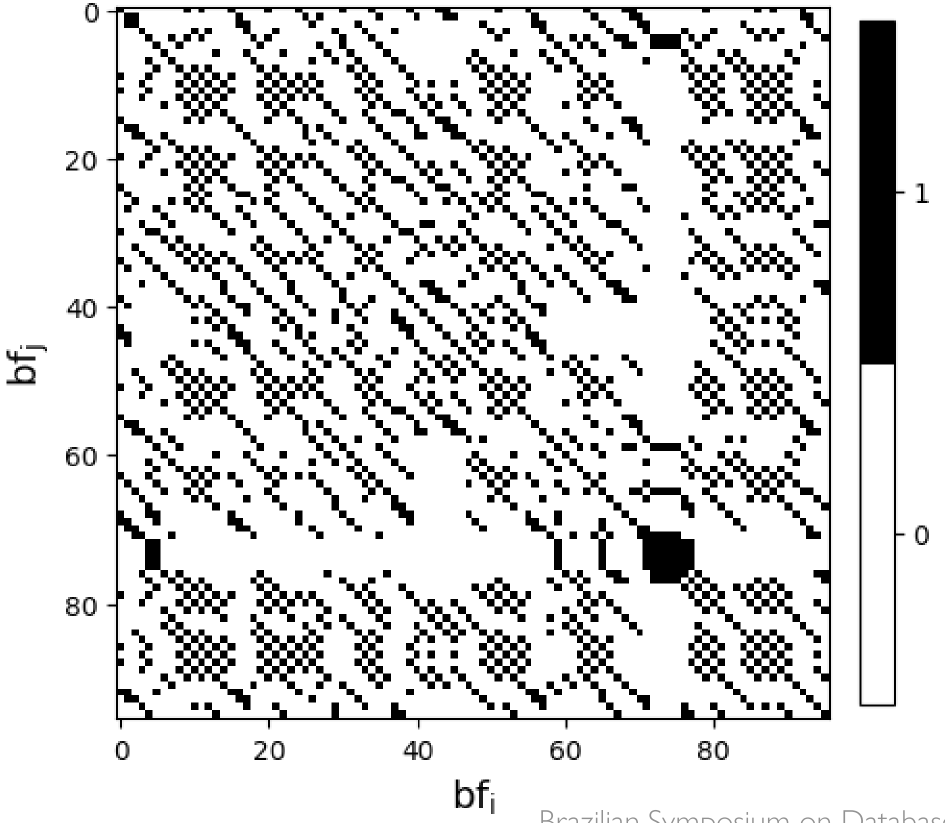


$l = 8, m = 3, \alpha = 1$

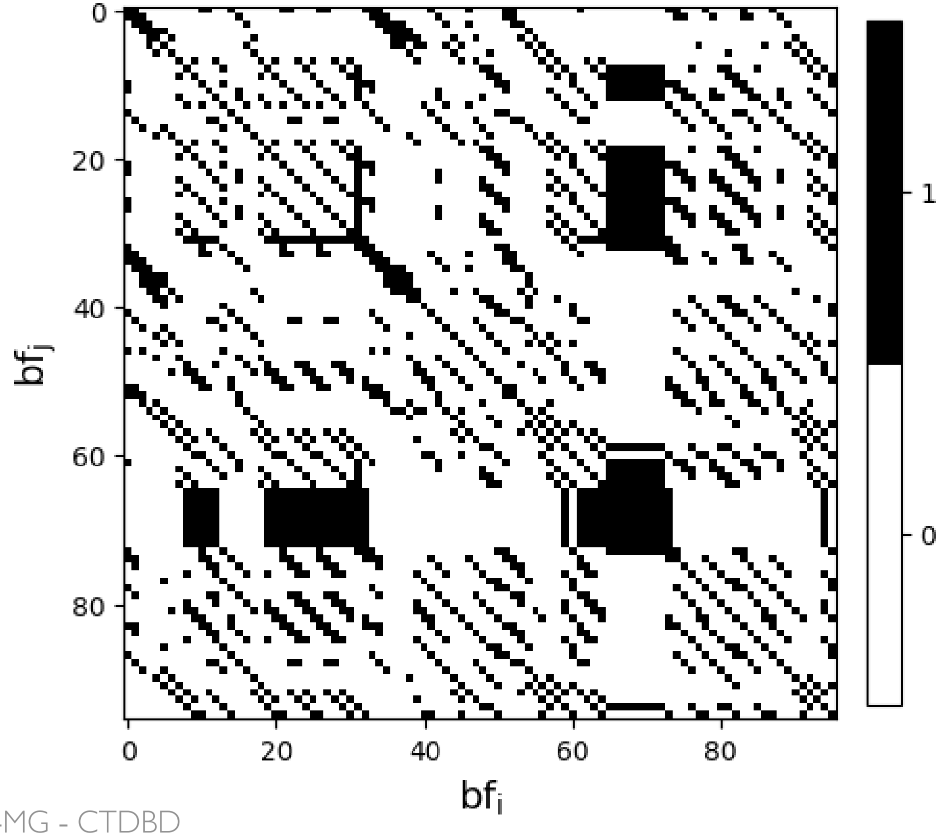
DLC

Real world Example Bloom Filter as a CRP

Matching BF pair

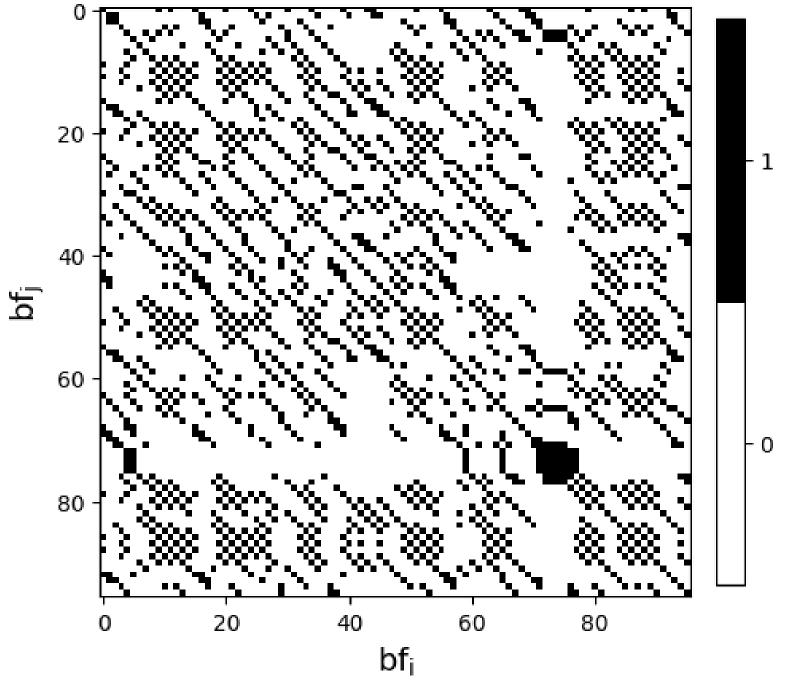


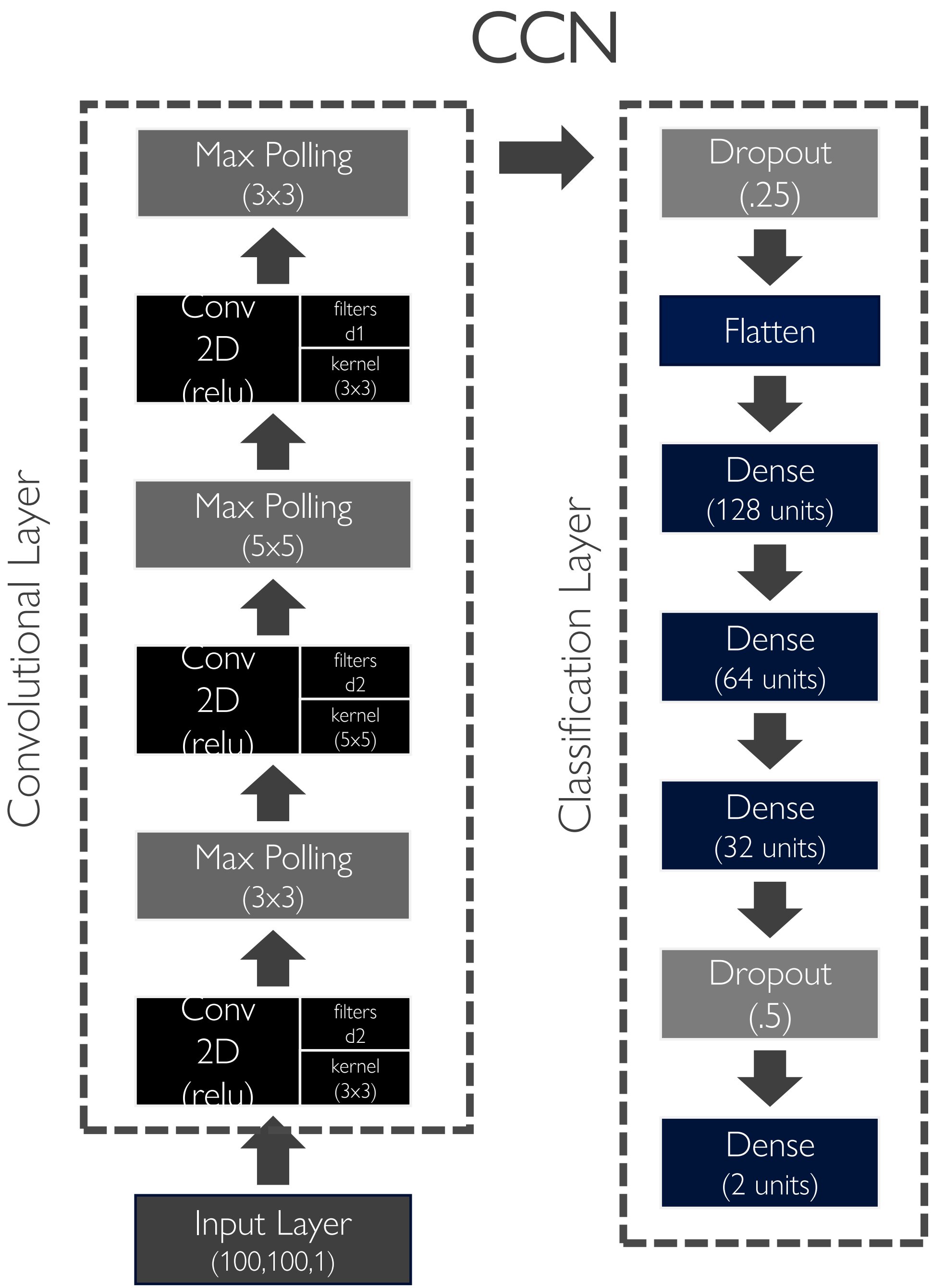
Non-Matching BF Pair



DLC

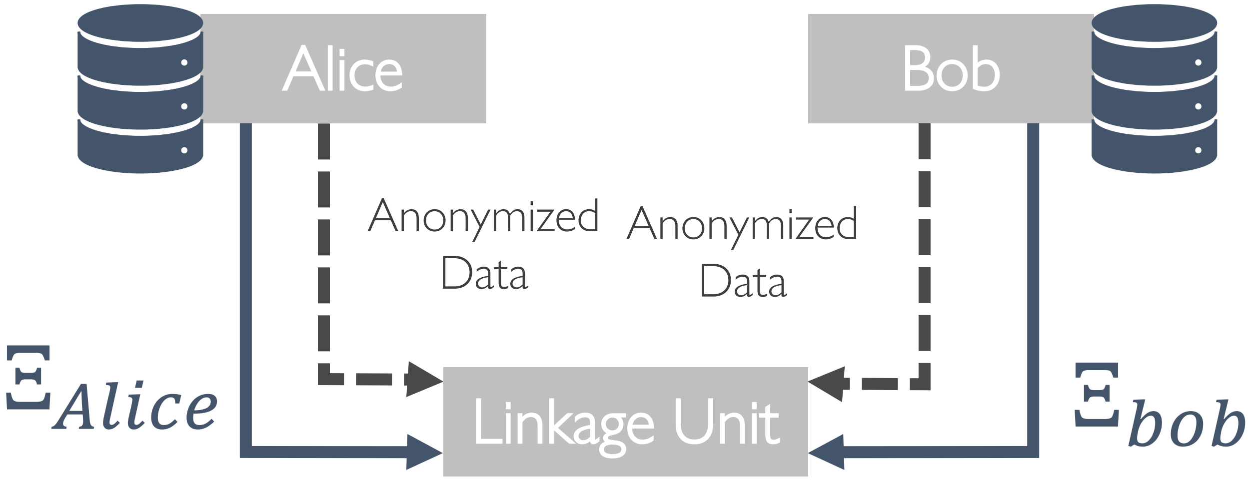
Convolution Neural Network Model





DLC

MHT Workflow



EVALUATION

DLC Linkage Quality and Privacy

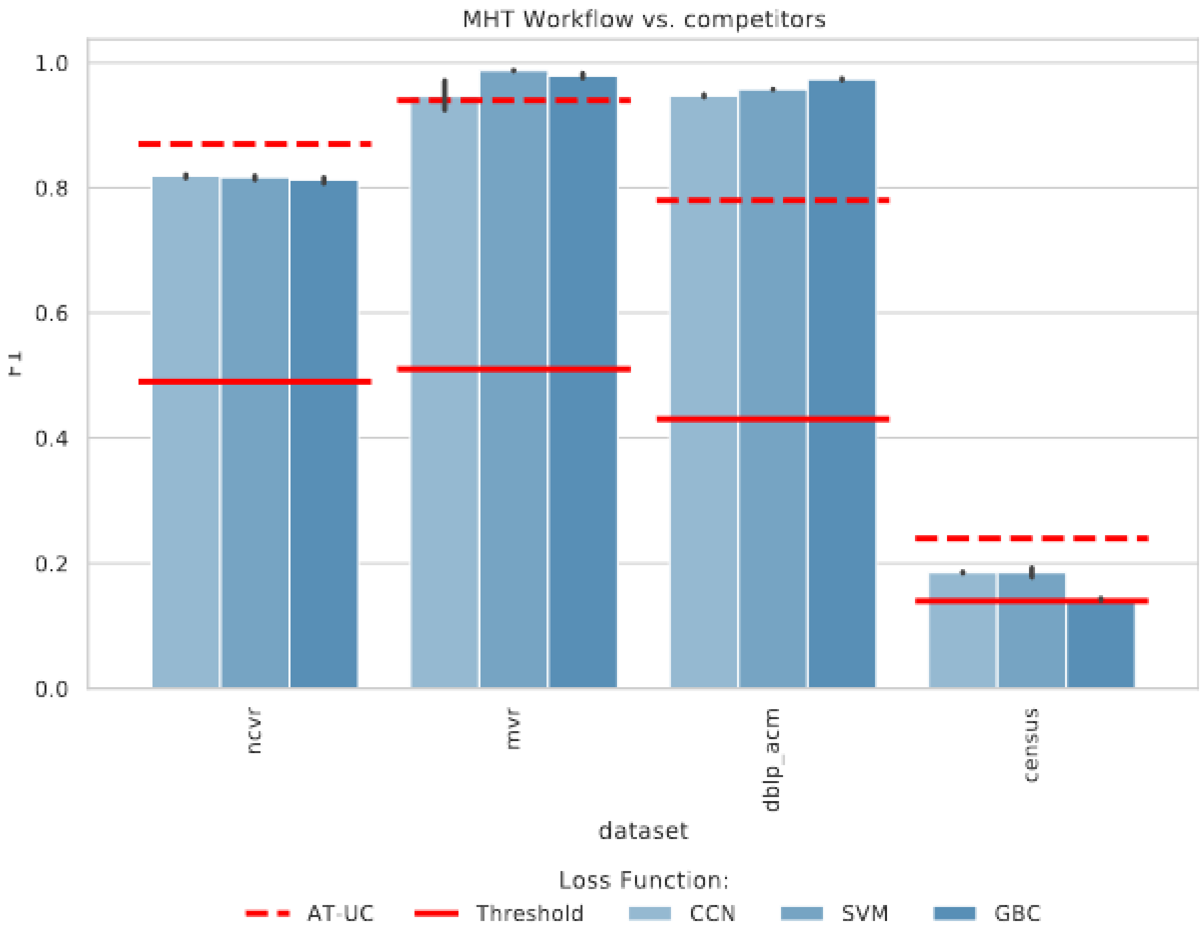
Evaluation Metrics

Linkage Quality

- DLC Quality Evaluation
  - Is CRP able to improve the classifiers effectiveness?
    - F1
  - What is the impact of using different classifiers in the MHT Workflow?
    - ROC Curve

Linkage Quality

Is DLC able to improve the PPRL quality results compared to the baseline and the competitor?



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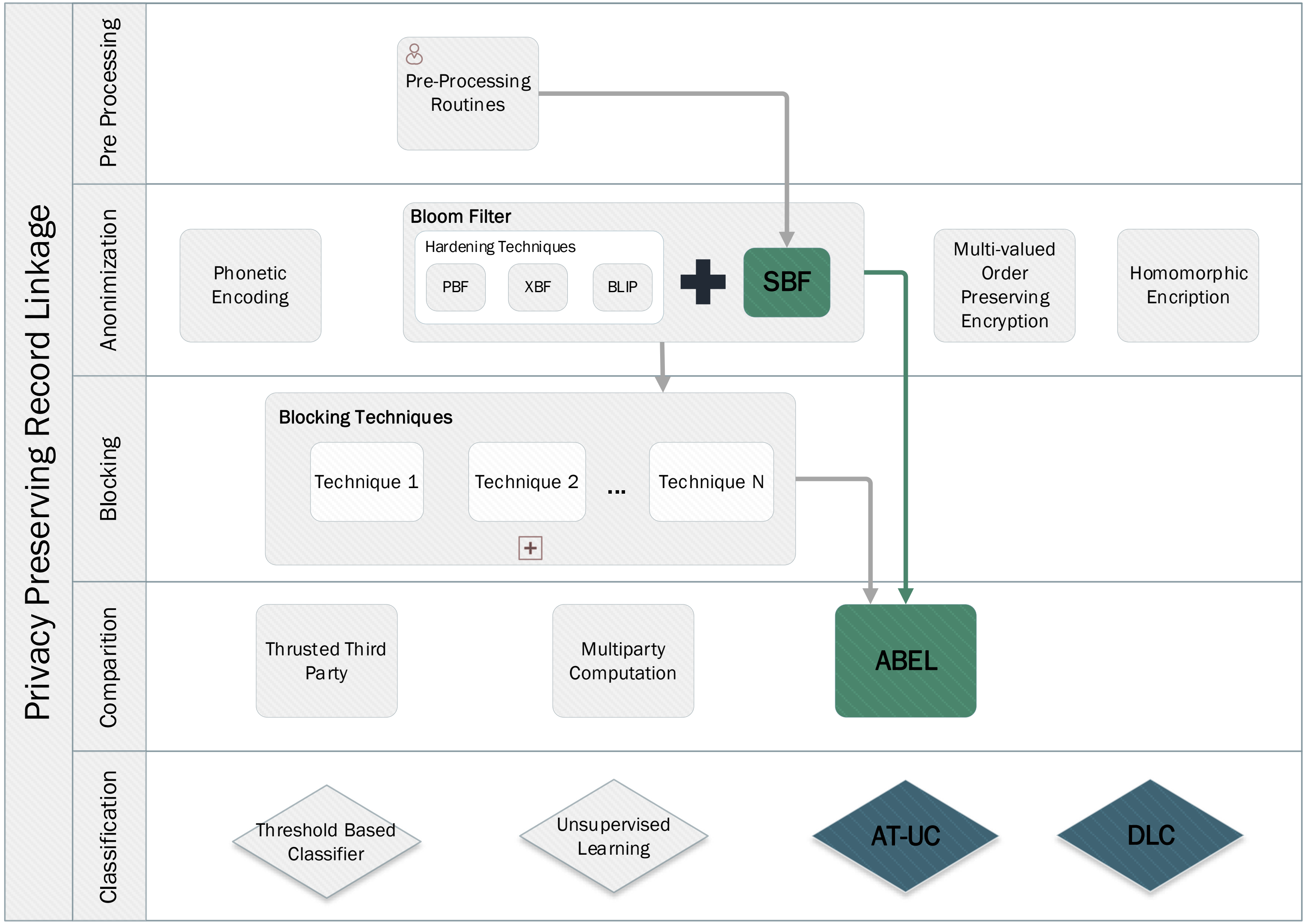
Final Arguments

Contributions



Code and Datasets

Available on author's github (https://github.com/thiagonobrega) :

i. Source Code
ii. Instructions*
iii. Datasets

* Reproducibility details

Research Relevance

Privacy Preserving Applications

- Medical
- Nacional Security
- Public Policies
- Novel Privacy Atacks

Other context

- Federated Linkage
- Census
- Identity Management
- Law and Regulations

Publications

i. Blockchain-based privacy-preserving record linkage: enhancing data privacy in an untrusted environment - T Nóbrega, CES Pires, DC Nascimento. Information Systems 102, 101826 - 2021

ii. Limitation of Blockchain-based Privacy-Preserving Record Linkage - T Nóbrega, CES Pires, DC Nascimento. Information Systems 108, 101935 - 2022

iii. Towards Auditable and Intelligent Privacy-Preserving Record Linkage - T Nóbrega, CES Pires, DC Nascimento. Anais Estendidos do XXXVI Simpósio Brasileiro de Bancos de Dados, 99-105S – 2020

iv. Towards automatic Privacy-Preserving Record Linkage: A Transfer Learning based classification step - T Nóbrega, CES Pires, DC Nascimento. Data & Knowledge Engineering 145 (2023): 102180.

* The publication of DLC is currently being written for submission.

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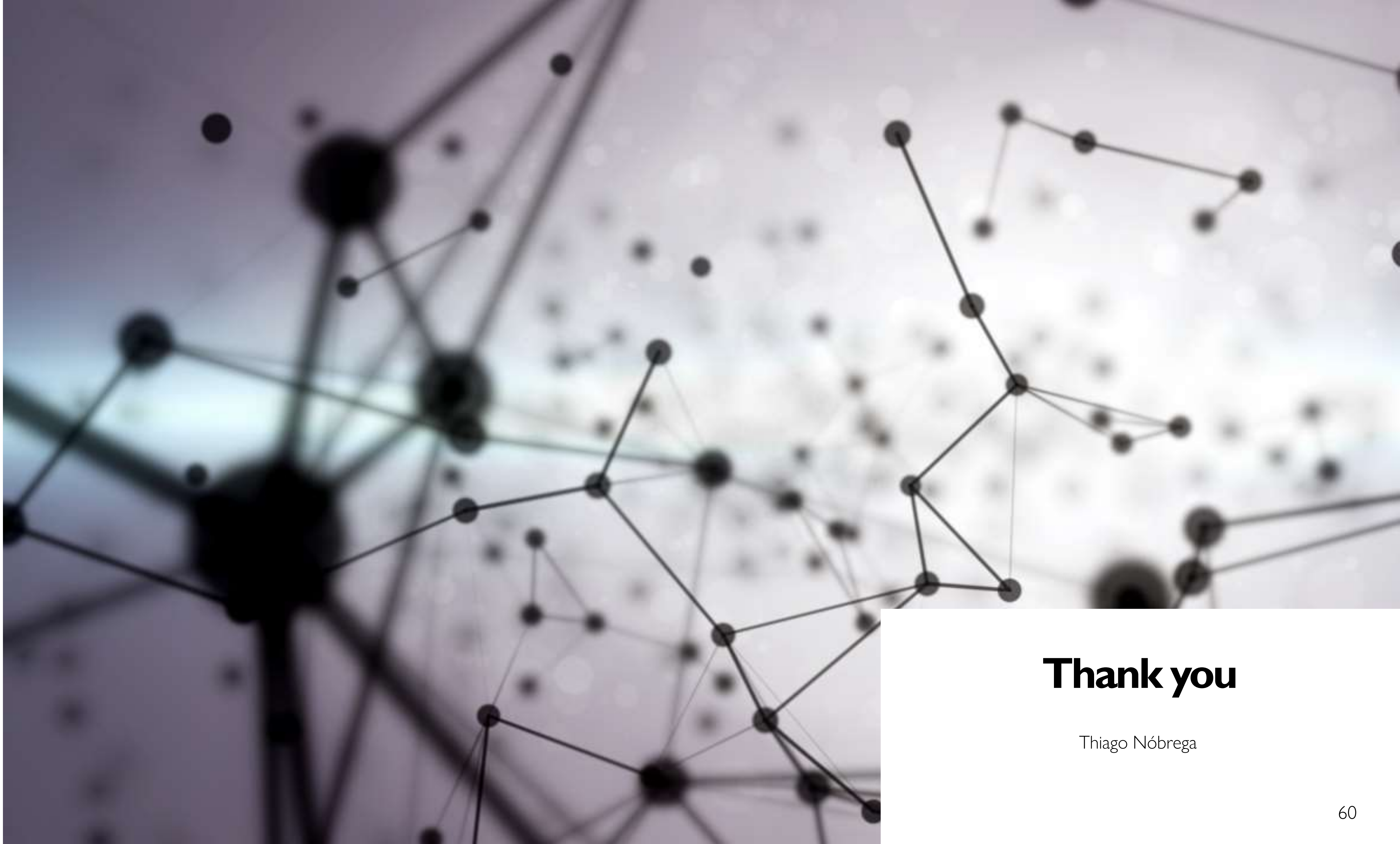
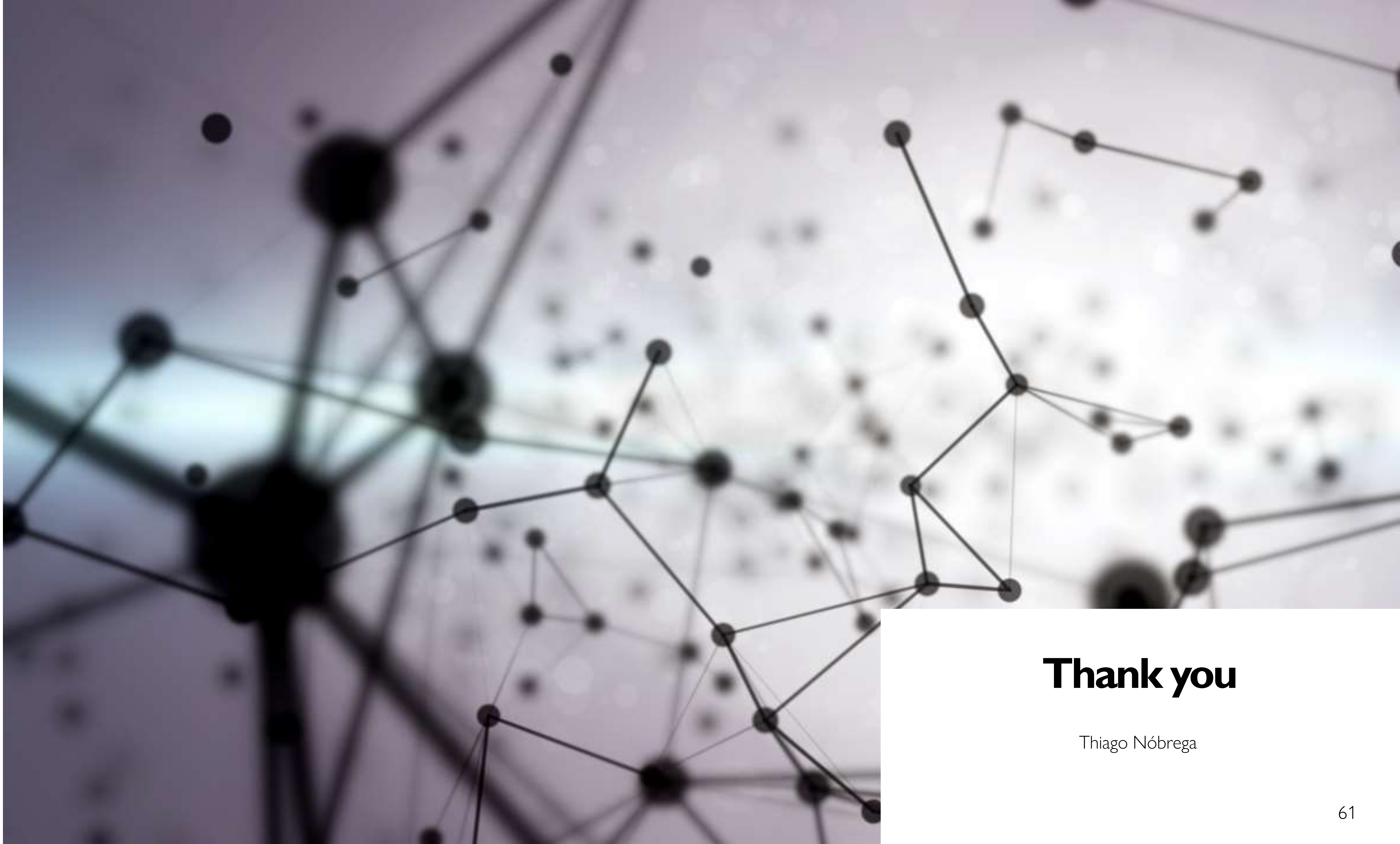


Thank you

Thiago Nóbrega

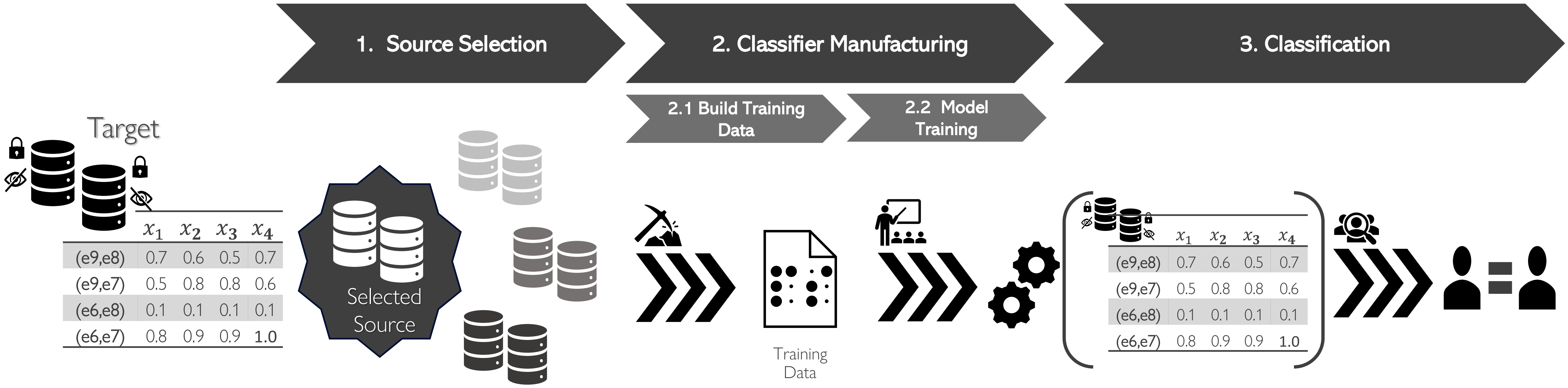


Thank you

Thiago Nóbrega

AT-UC Overview

Three stage approach



	x_1	x_2	x_3	x_4
(e9,e8)	0.7	0.6	0.5	0.7
(e9,e7)	0.5	0.8	0.8	0.6
(e6,e8)	0.1	0.1	0.1	0.1
(e6,e7)	0.8	0.9	0.9	**1.0**

	x_1	x_2	x_3	x_4
(e9,e8)	0.7	0.6	0.5	0.7
(e9,e7)	0.5	0.8	0.8	0.6
(e6,e8)	0.1	0.1	0.1	0.1
(e6,e7)	0.8	0.9	0.9	**1.0**

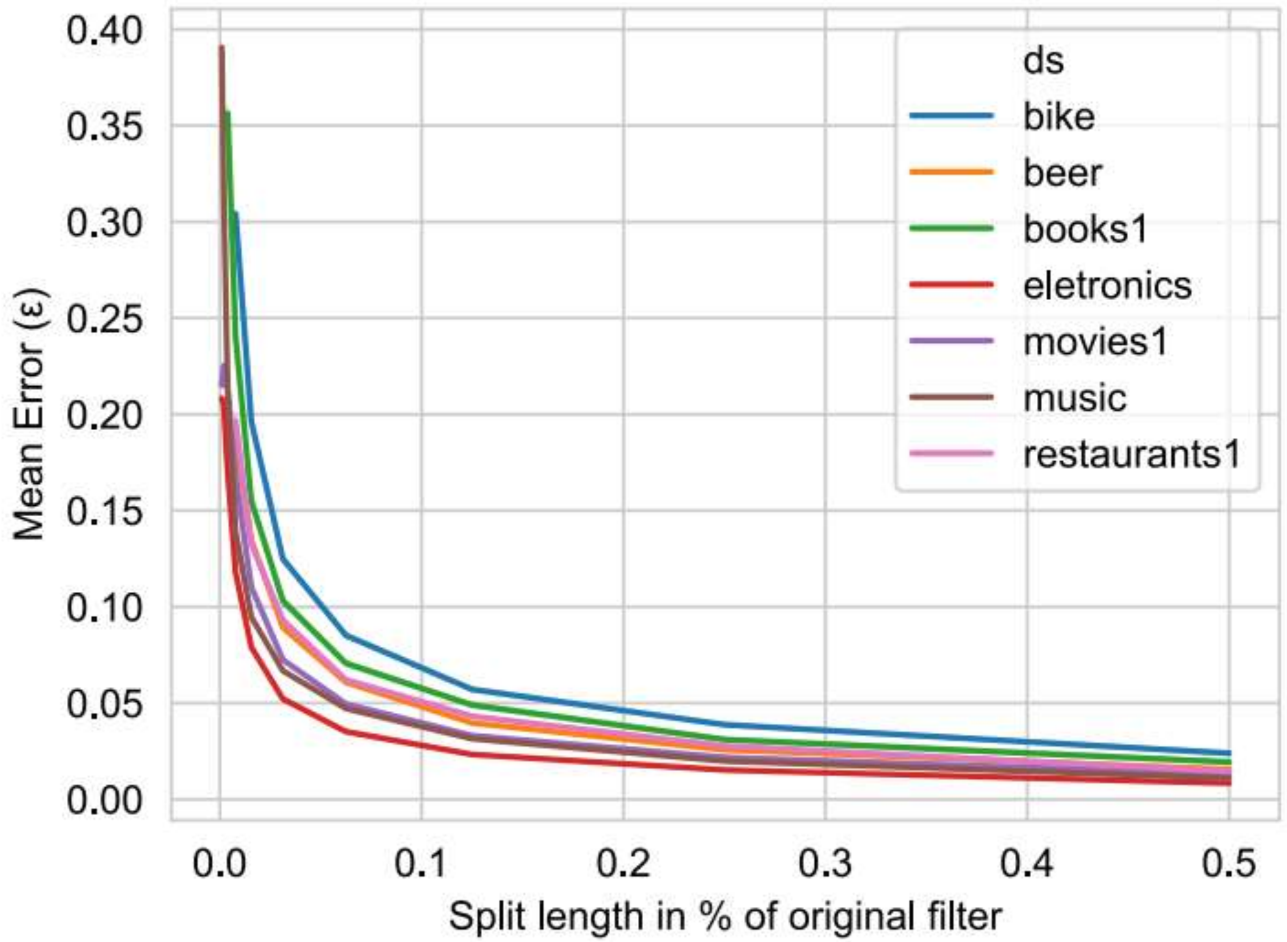
Future Work

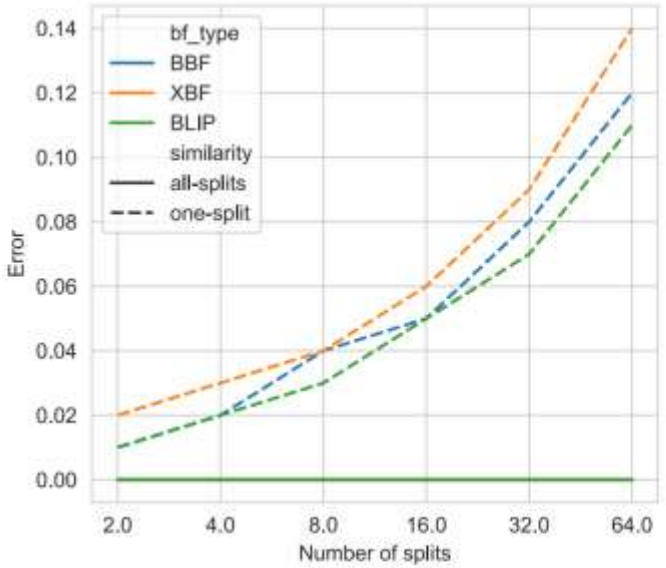
- Privacy aspects
  - Improve the privacy guarantees of the PPRL process (Privacy-Preserving Blockchain)
  - Novel Privacy Attacks
  - Differential Privacy in PPRL
- Linkage Quality and Novel PPRL Applications
  - Distributed Representation of Words (DR) in PPRL
  - Federated Learning (collaborative learning)
  - Deep Unsupervised Domain Adaptation

Research goals

“This work’s main goal covers improving privacy and the linkage quality of PPRL process”

SBF ERROR





$$B\left(\frac{l}{s}, p\right) = \binom{\frac{l}{s}}{x} p^x (1-p)^{\frac{l}{s}-x}$$

SBF Goal

[1 1 0 1], [0 1 0 1], [1 1 0 0]   [1 1 0 1], [1 1 0 1], [0 1 1 0]

$$threshold = .65 | \epsilon \cong 0.35$$

$$Jaccard(\ [1\ 1\ 0\ 1]\ ,\ [1\ 1\ 0\ 1]\ ) = \frac{3}{3} \to 1 \quad | \epsilon \cong 0.35$$

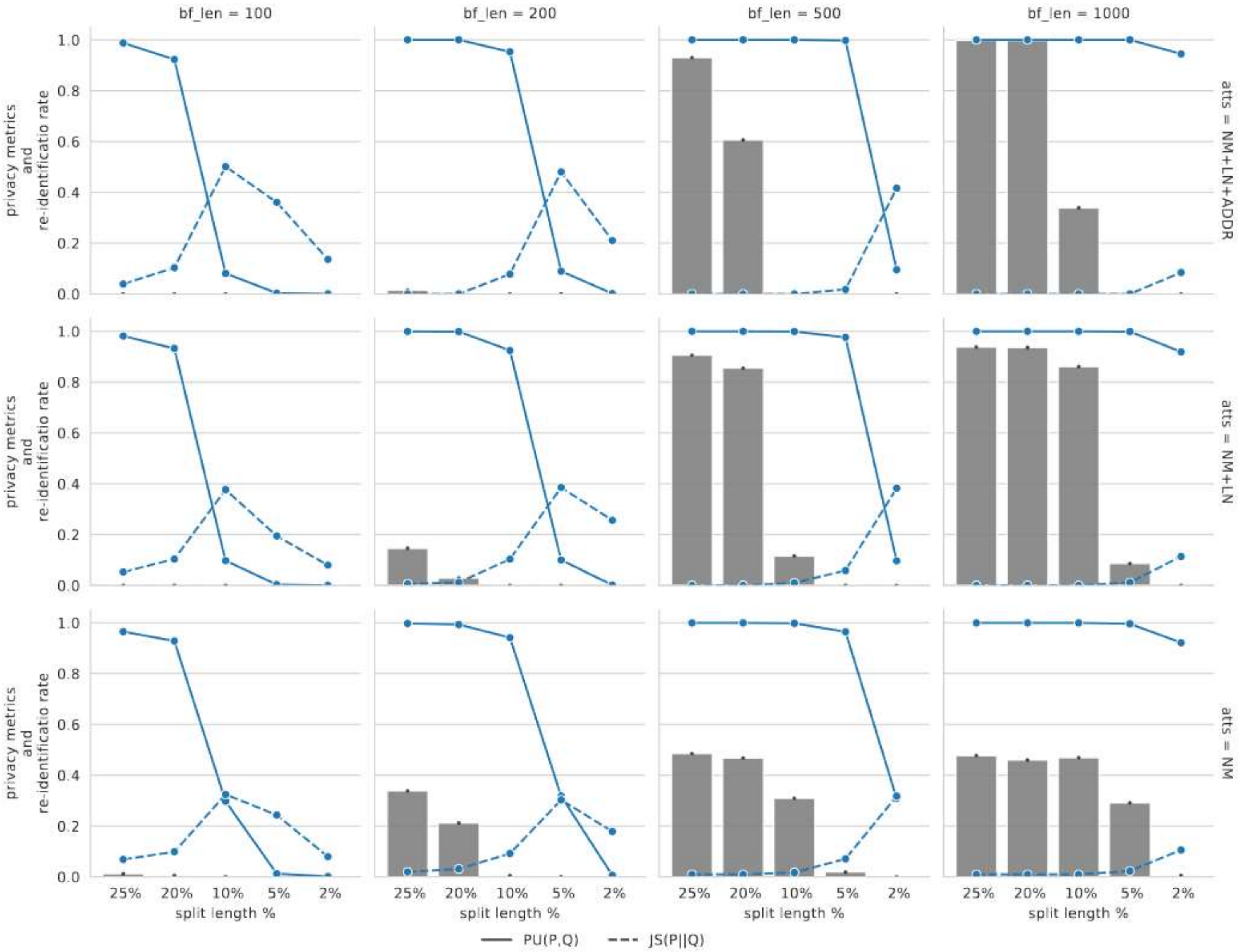
$$Jaccard(\ [0\ 1\ 0\ 1]\ ,\ [1\ 1\ 0\ 1]\ ) = \frac{2}{3} \to 0.65 | \epsilon \cong 0.0$$

$$Jaccard(\ [1\ 1\ 0\ 0]\ ,\ [0\ 1\ 1\ 0]\ ) = \frac{1}{3} \to 0.3 \quad | \epsilon \cong 0.35$$

Privacy

ABEL Parametrization

- *Indistinguishability*
  - $PU(P,Q) < 0.5$
- Uncertain
  - $KL(P,Q) > 0.1$

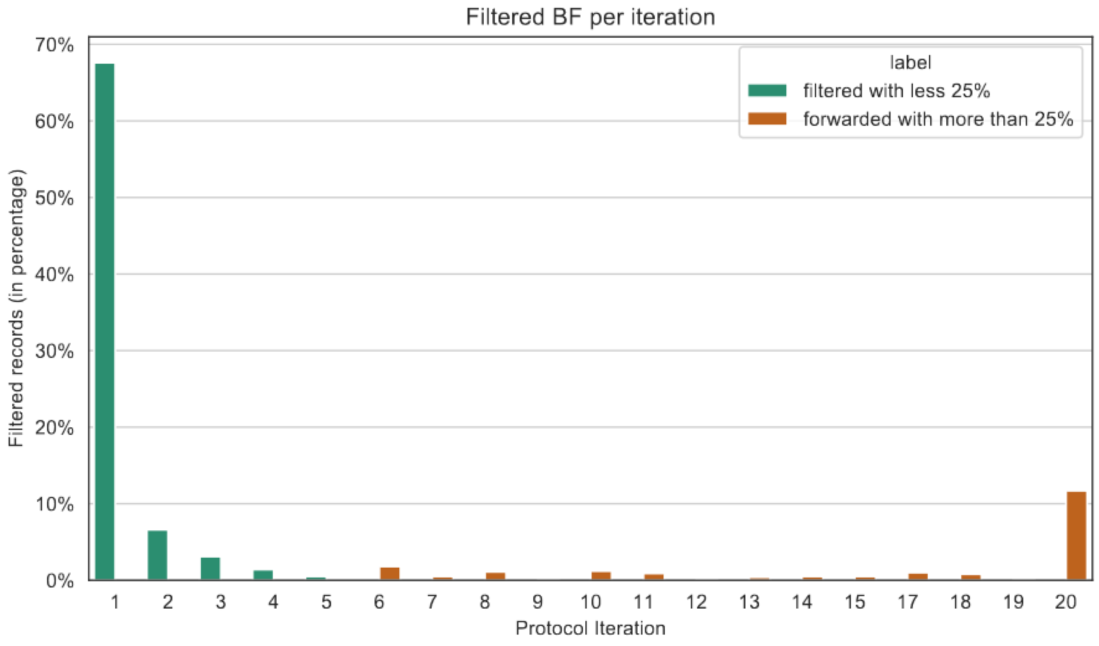


Privacy

Attack Effectiveness

Test parameters

- Dataset : NCVR
- Bloom Filter
  - l = 200 bits
  - f.p.r = 50%
- ABEL
  - *Privacy parameters*
    - *Indistinguishability*
      - $PU(P,Q) < 0.5$
    - Uncertain
      - $KL(P,Q) > 0.1$
  - *a = .85 , error = .05*
  - *s = 10 bits (5%)*



iteration	shared information	1-to-1 correct	1-to-many correct	1-to-1 wrong	1-to-many wrong	No matches
Iteration 1	5%	1	0	5,588	4,411	0
Iteration 2	10%	1	1	1,855	1,392	0
Iteration 3	15%	8	17	1,157	975	0
Iteration 4	20%	48	137	804	759	0
Iteration 5	25%	214	312	614	450	0
Iteration 6-20	100%	1,346	125	0	0	0

Research questions

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II. Is it possible to consider a novel adversary model that reduces the need of thrust by PPRL parties?

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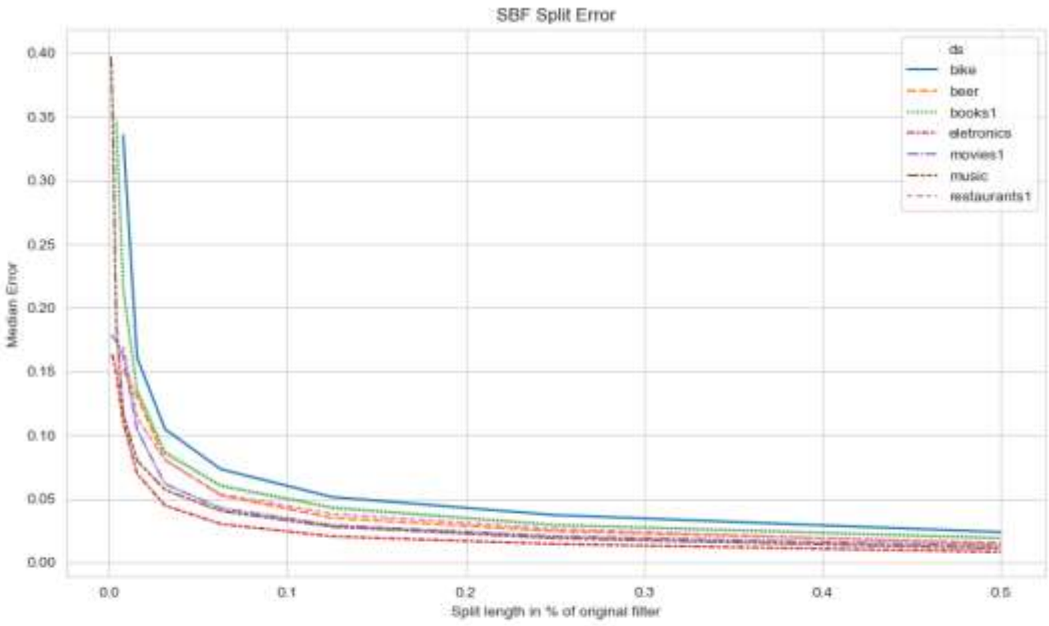
SBF

Shared Information

ANA ANE

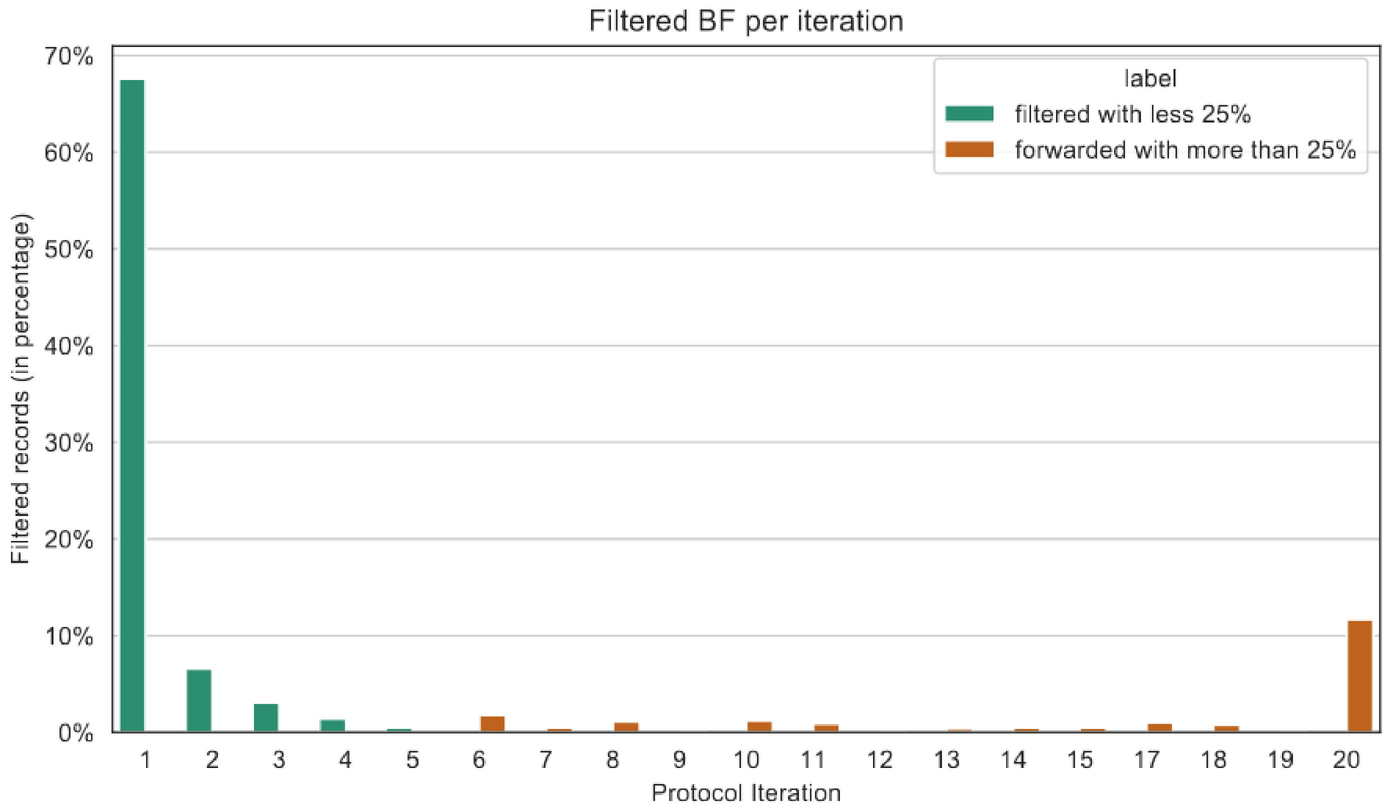
$$Jaccard(\boxed{1\,1\,0\,1\,0\,1\,0\,1\,1\,1\,0\,0}, \boxed{1\,1\,0\,1\,1\,1\,0\,1\,0\,1\,1\,0}) = Jaccard(\boxed{1\,1\,0\,1}, \boxed{1\,1\,0\,1}) + \boldsymbol{error}$$



$$\boldsymbol{error} = \binom{\frac{l}{s}}{x} p^x (1-p)^{\frac{l}{s}-x}$$

SBF

Privacy Motivation



- Split Filtering
- Indistinguishability
- Uncertainty

Linkage Quality

What is the impact of using different classifiers - e.g., state-of-the-art NN (ResNet50) and classical Machine Learning classifiers (SVM and GBC) - in the MHT Workflow?

dataset	model	precision	recall	f1
census	CCN	87.23% ±0.0	10.38% ±0.08	18.55% ±0.13
	GBC	69.86% ±1.5	7.94% ±0.13	14.26% ±0.25
	SVM	95.74% ±6.02	10.27% ±0.58	18.55% ±1.06
dblp_acm	CCN	98.95% ±0.34	90.82% ±0.19	94.71% ±0.26
	GBC	97.12% ±0.65	97.6% ±1.07	97.35% ±0.21
	SVM	93.4% ±0.04	98.21% ±0.04	95.74% ±0.04
mvr	CCN	99.12% ±1.04	90.63% ±3.87	94.66% ±2.36
	GBC	100.0% ±0.0	95.91% ±1.06	97.91% ±0.55
	SVM	100.0% ±0.0	97.52% ±0.14	98.75% ±0.07
ncvr	CCN	69.47% ±0.52	99.76% ±0.22	81.9% ±0.29
	GBC	68.52% ±0.76	99.9% ±0.09	81.28% ±0.51
	SVM	69.09% ±0.55	99.9% ±0.08	81.69% ±0.36