MEDI-CHAL PRESENTATION

REVIEW OF METRICS FOR SYNTHETIC DATA : PRIVACY AND UTILITY TRADEOFFS

- SALONI DASH

OVERVIEW

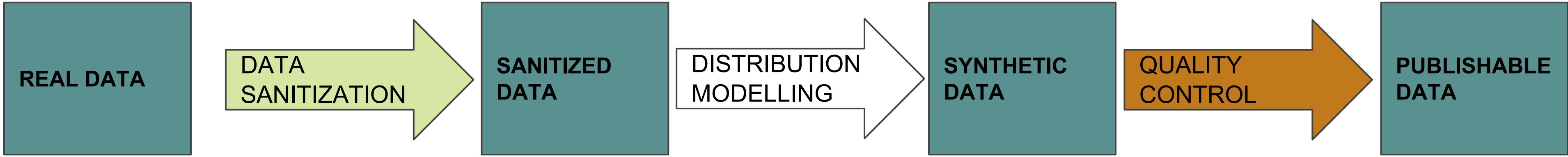
- DATA PUBLISHING CONTEXT
- PRIVACY
  - WHAT IS PRIVACY?
  - PRIVACY PRESERVING TECHNIQUES
  - PRIVACY REQUIREMENTS
- PRIVACY VS DATA UTILITY
  - WHAT IS DATA UTILITY?
  - GENERAL METHODOLOGY
  - DIRECT COMPARISON METHOD
  - EXPERIMENTAL RESULTS
  - CRITICISM OF DIRECT COMPARISON
- CONCLUSION
- REFERENCES

LINK TO PREVIOUS TALK

A STUDY OF PRIVACY METRICS :

https://docs.google.com/presentation/d/1JEBJh3VKOj6XGFcn3_8N584nxO0VDrqMAGRCV4ok6PQ/edit?usp=sharing

DATA PUBLISHING CONTEXT



PRIVACY

WHAT IS PRIVACY?

- In the context of Data Publishing :
    - Organization has confidential records of individuals
- Attack Scenarios :
    - Adversary has QIDs of an individual
    - Adversary builds classifier for sensitive attributes
- Data Anonymization Goals :
    - **Unique Identity Disclosure**
    - **Sensitive Attribute Disclosure**

Key Attribute	Quasi-identifier			Sensitive attribute
Name	DOB	Gender	Zipcode	Disease
Andre	1/21/76	Male	53715	Heart Disease
Beth	4/13/86	Female	53715	Hepatitis
Carol	2/28/76	Male	53703	Brochitis
Dan	1/21/76	Male	53703	Broken Arm
Ellen	4/13/86	Female	53706	Flu
Eric	2/28/76	Female	53706	Hang Nail

PRIVACY PRESERVING TECHNIQUES

Name	Gender	Zip code	Age
Reena	Female	444805	45
Shweta	Female	424806	46
Kavita	Female	424806	58
Neha	Female	444806	65

ORIGINAL DATASET

- Generalization

Name	Gender	Zip code	Age
Reena	Person	444805	40-60
Shweta	Person	424806	40-60
Kavita	Person	424806	40-60
Neha	Person	444806	40-60

- Suppression

Gender	Zip code	Age	Disease
Female	444805	**	**
Female	424806	**	**
Female	424806	**	**
Female	444806	**	**

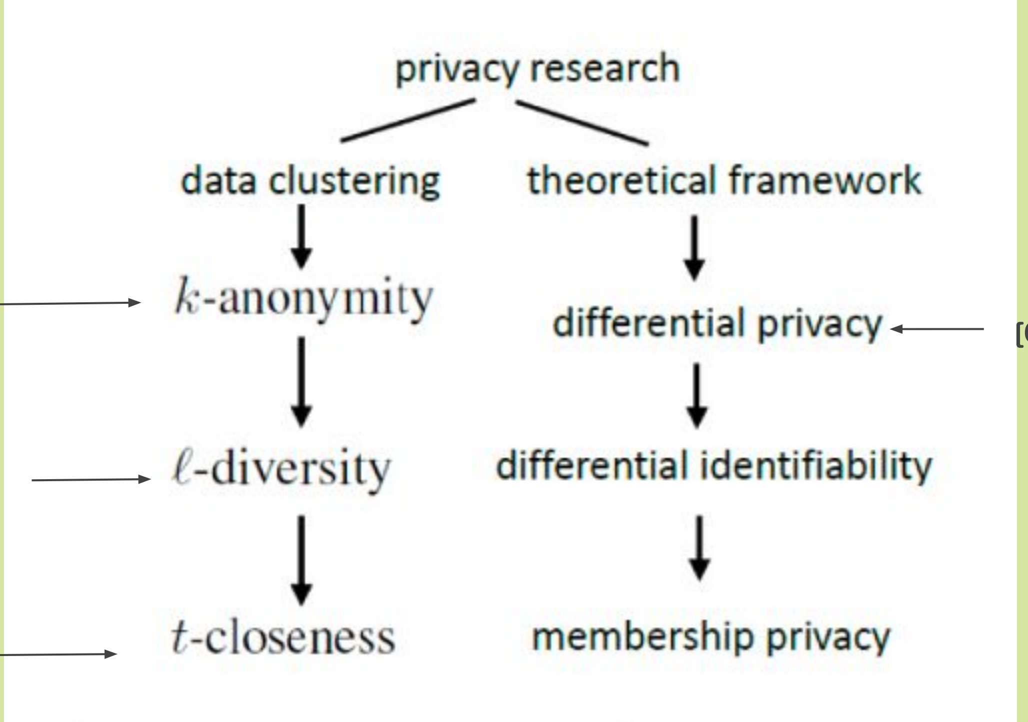
- Bucketization

Gender	Zip code	Age	GID
Female	444805	45	1
Female	424806	46	2
Female	424806	58	3
Female	444806	65	4

a) QId table

Disease	GID
TB	1
Diabetes	2
Fever	3
Cancer	4

CATEGORIES OF PRIVACY RESEARCH



[11] {L. Sweeney et al. , 1998}

[6]{Dwork, C et al. 2006}

[15]{A. Machanavajjhala et al. 2006}

[8]{N. Li et al. 2007}

PRIVACY REQUIREMENTS

- **k-anonymity :**
  - The identifiable attributes of any database record are indistinguishable from at least other k-1 records

	ZIP Code	Age	Disease
1	47677	29	Heart Disease
2	47602	22	Heart Disease
3	47678	27	Heart Disease
4	47905	43	Flu
5	47909	52	Heart Disease
6	47906	47	Cancer
7	47605	30	Heart Disease
8	47673	36	Cancer
9	47607	32	Cancer

Table 1. Original Patients Table

	ZIP Code	Age	Disease
1	476**	2*	Heart Disease
2	476**	2*	Heart Disease
3	476**	2*	Heart Disease
4	4790*	≥ 40	Flu
5	4790*	≥ 40	Heart Disease
6	4790*	≥ 40	Cancer
7	476**	3*	Heart Disease
8	476**	3*	Cancer
9	476**	3*	Cancer

Table 2. A 3-Anonymous Version of Table 1

- **l-diversity :**
  - Every equivalence class should abide by the l-diversity principle

Bob	
Zip	***Age***
47678	27

A 3-diverse patient table

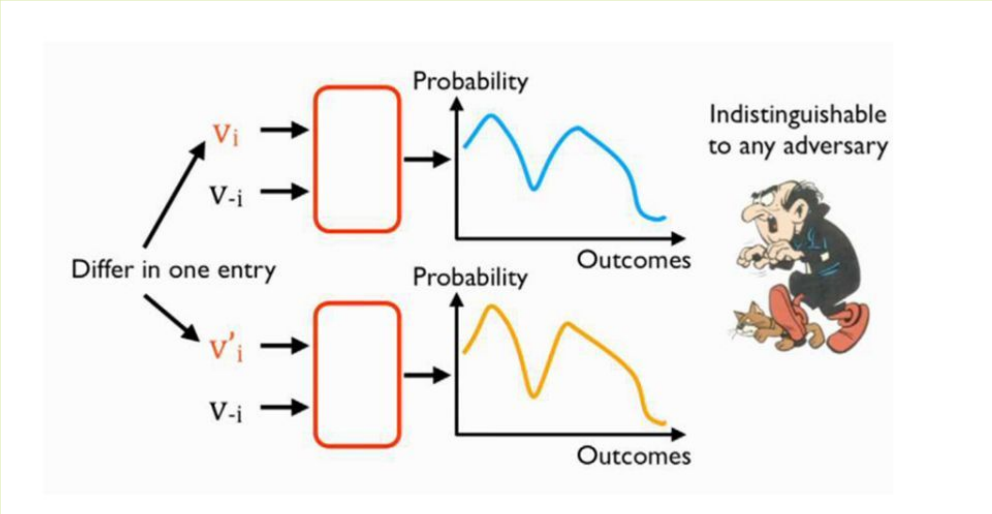
Zipcode	Age	Salary	Disease
476**	2*	20K	Gastric Ulcer
476**	2*	30K	Gastritis
476**	2*	40K	Stomach Cancer
4790*	≥40	50K	Gastritis
4790*	≥40	100K	Flu
4790*	≥40	70K	Bronchitis
476**	3*	60K	Bronchitis
476**	3*	80K	Pneumonia
476**	3*	90K	Stomach Cancer

- **t-closeness:**
  - Distance between the distribution of a sensitive attribute in the original table and the distribution of the same attribute in any equivalence class is less or equal to t

	ZIP Code	Age	Salary	Disease
1	4767*	≤ 40	3K	gastric ulcer
3	4767*	≤ 40	5K	stomach cancer
8	4767*	≤ 40	9K	pneumonia
4	4790*	≥ 40	6K	gastritis
5	4790*	≥ 40	11K	flu
6	4790*	≥ 40	8K	bronchitis
2	4760*	≤ 40	4K	gastritis
7	4760*	≤ 40	7K	bronchitis
9	4760*	≤ 40	10K	stomach cancer

Table 5. Table that has 0.167-closeness w.r.t. Salary and 0.278-closeness w.r.t. Disease

- **Differential privacy :**
  - Measure the difference on individual privacy disclosure between the presence and the absence of the individual’s record.
  - Ensures that a single record does not considerably affect the outcome of the analysis over the dataset



PRIVACY VS UTILITY

WHAT IS DATA UTILITY?

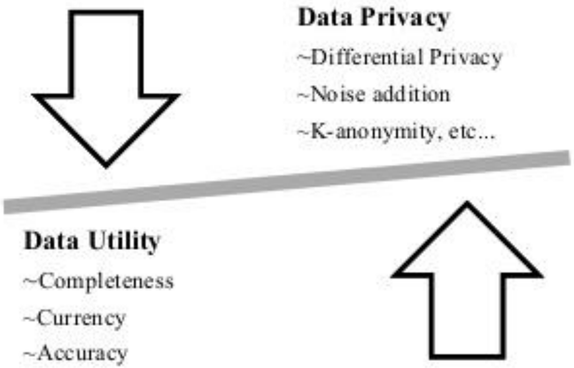
- Gains to society from data publishing:
  - Enables **researchers** and **policy-makers** to analyze the data
  - Important information benefiting the society as a whole can be learned :
    - Diseases
    - Effectiveness of a medicine or treatment
    - Social-economic patterns
- Data Utility Preservation Metrics (Ritik’s talk)
  - For e.g., K.S. tests, Comparison of Covariance Matrices etc.

BALANCING PRIVACY & UTILITY

THE PROBLEM

Finding a user-defined balance between data privacy and utility needs with trade-offs.

- The challenge of ambiguous definitions of privacy and utility.

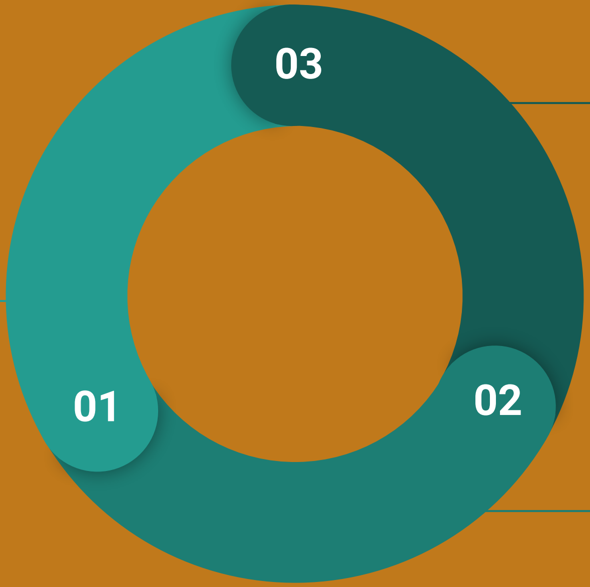


"Perfect privacy can be achieved by publishing nothing at all, but this has no utility; perfect utility can be obtained by publishing the data exactly as received, but this offers no privacy" Cynthia Dwork (2006)

GENERAL METHODOLOGY

PRIVACY REQUIREMENT:

- k-ANONYMITY
- l-DIVERSITY
- t-CLOSENESS
- DIFFERENTIAL PRIVACY



UTILITY METRIC:
- K.S. TESTS
- COMPARISON OF COVARIANCE MATRICES

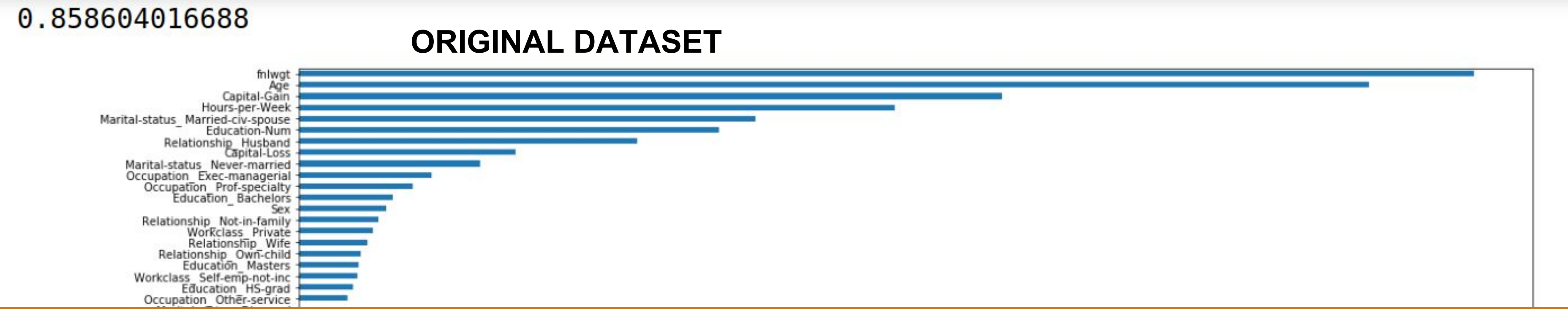
PRIVACY PRESERVING ALGORITHM:

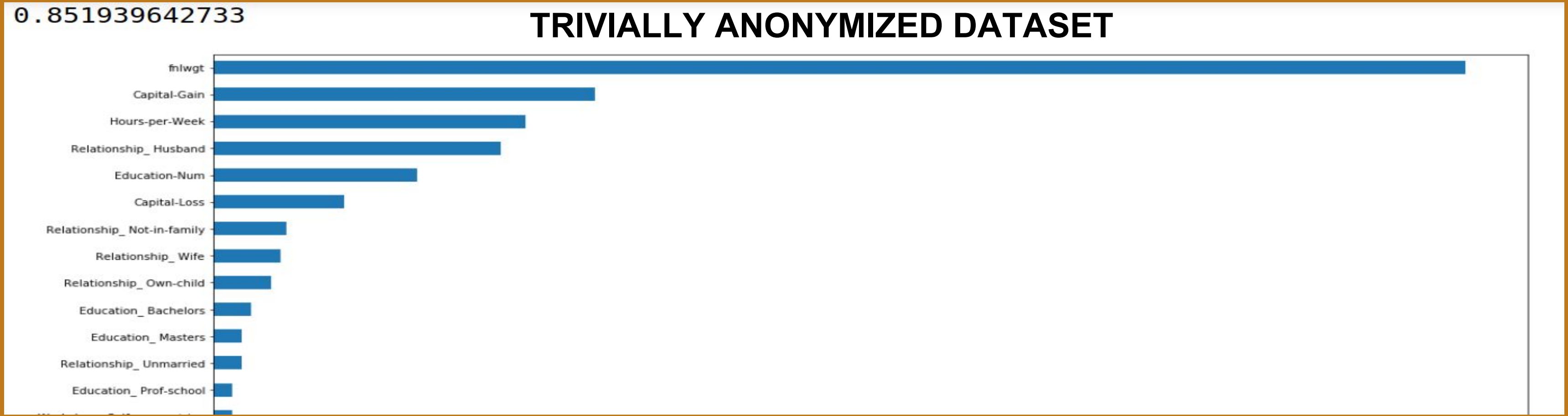
- GENERALIZATION
- SUPPRESSION
- BUCKETIZATION

DIRECT COMPARISON {J. Brickell et al.}

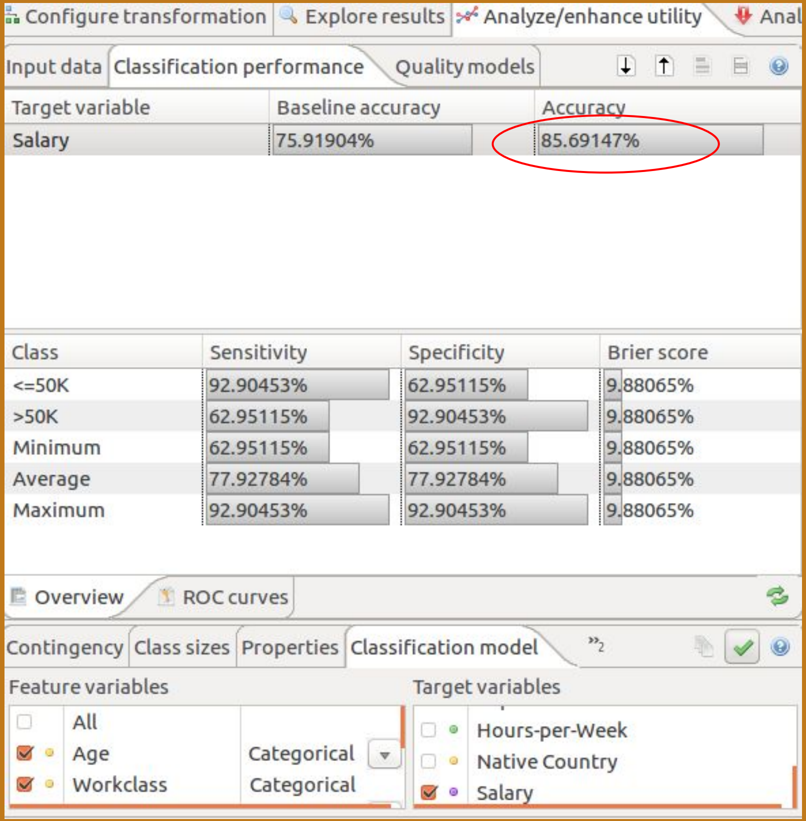
- Privacy loss is measured as the adversary's accuracy improvement in guessing the sensitive attribute value of an individual
- Utility gain is measured as the researcher's accuracy improvement in building a classification model for the sensitive attribute.
- Privacy Loss as well as Data Utility measured against trivialised anonymized dataset.
- Experiments in [18]{J. Brickell and V. Shmatikov.} leads to the intriguing conclusion "even modest privacy gains require almost complete destruction of the data-mining utility

EXPERIMENTAL RESULTS



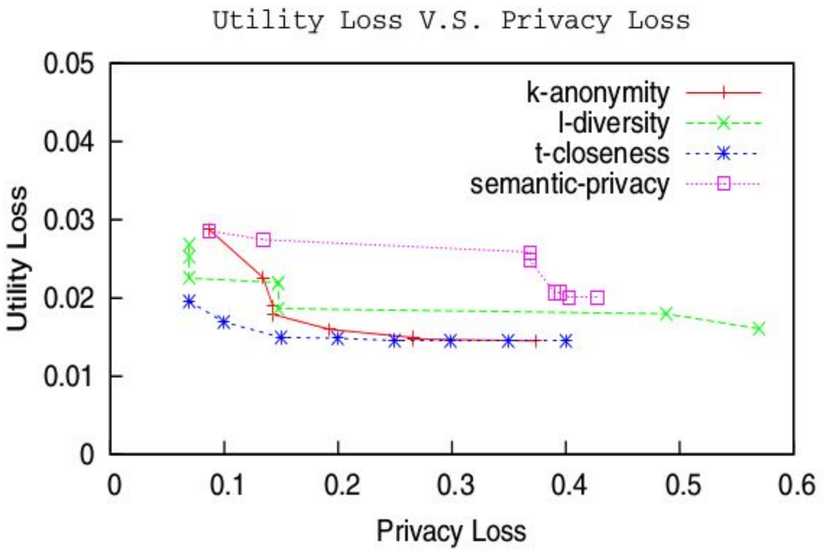


5-ANONYMIZED + 0.001 CLOSE DATASET

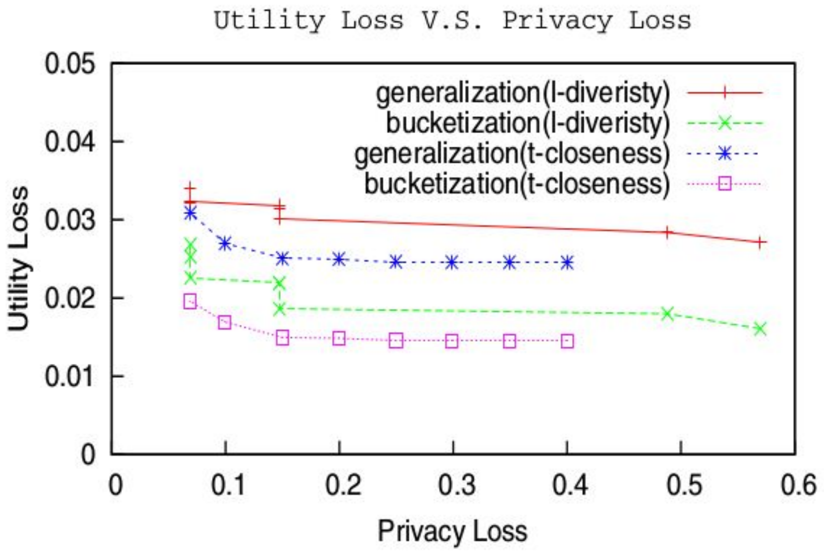


CRITICISM OF DIRECT METHODOLOGY [18]{T. Li et. al, 2009}

- Specific knowledge has a larger impact on privacy, while aggregate information has a larger impact on utility.
- Privacy is an Individual concept, while utility is an aggregate concept
- For privacy, the worst-case privacy loss should be measured. For utility, the aggregated utility should be measured.
- Data utility should be measured against original dataset.



(a) Varied privacy requirements

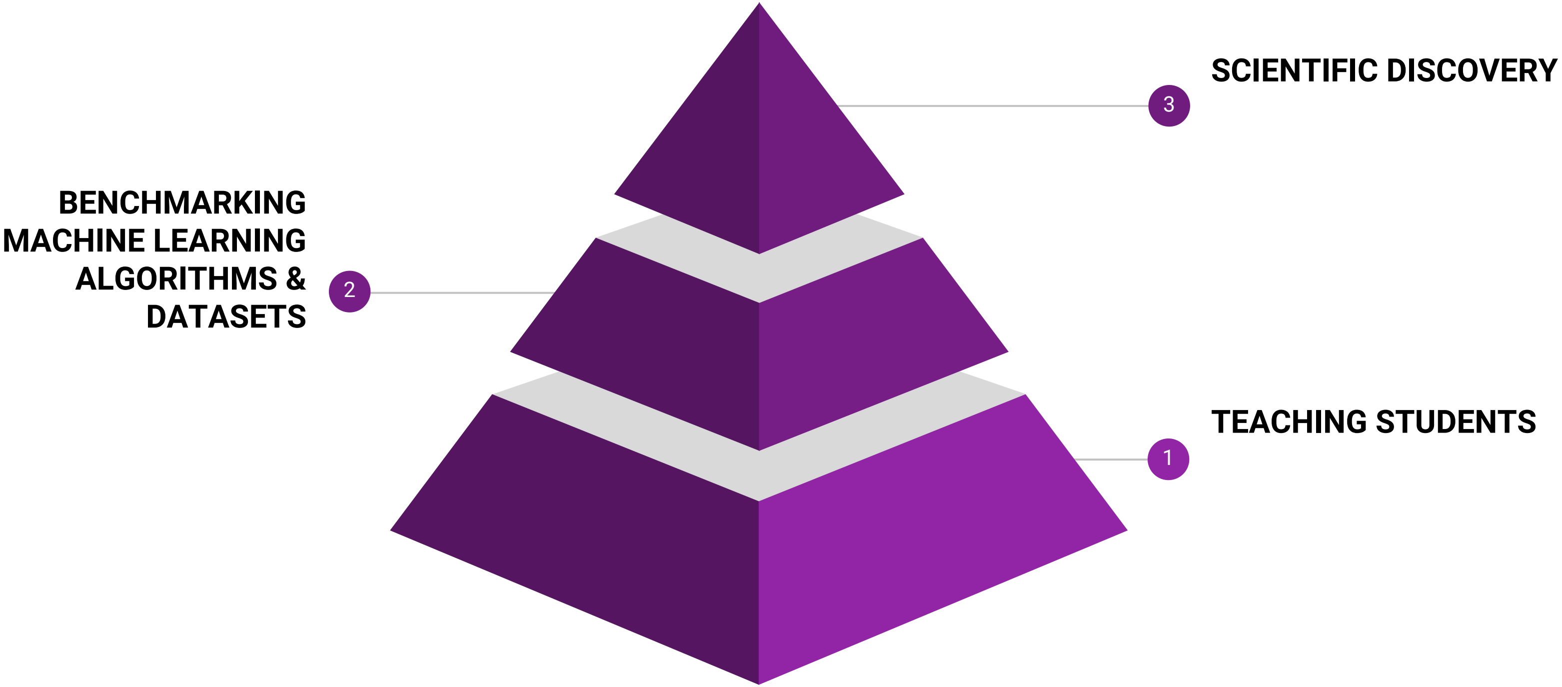


(b) Varied anonymization methods

Distance Metric : J.S. Divergence

CONCLUSION

SYNTHETIC DATA UTILITIES



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THANK YOU!