Modernizing Education Data Systems through Privacy Enhancing Technologies (PETs)

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Education Data Ecosystem





What Protects Privacy Now?

- Lockdowns (don't trust anyone)
- Trusted third parties (limited/earned trust)
- Contracts (licenses, NDAs, MOUs)
- Statistical disclosure controls
 - Rounding, swapping, suppression, etc.

What Are Privacy Enhancing Technologies (PETs)?

- Cryptographic techniques that increase data protection while allowing for greater data utility
- Can enhance how data are analyzed and/or published
- Can complement or replace other statistical disclosure limitation methods





Two Aspect of Privacy

- Input privacy
 - Data access or sharing challenges
 - Reduces risks of unauthorized access or inappropriate use
- Output privacy
 - Results of data analysis, such as information in tables or graphs
 - Reduces the risks of re-identification of data subjects



Is Anyone Using PETs?

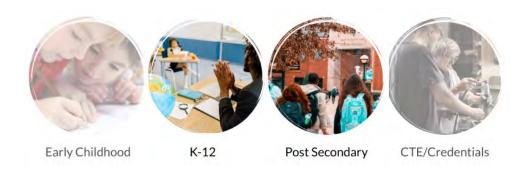
		Ongoing?		PPTs in Education	
le 3. PPTs i	n Education Project Birth through Eight Strategy for Tulsa (BEST) with Tulsa Public Distribution of the strategy for Tulsa (BEST) with Tulsa Public Birth through Eight Strategy for Tulsa (BEST) with Tulsa Public Birth through Eight Strategy for Tulsa (BEST) with Tulsa Public Birth through Eight Strategy for Tulsa (BEST) with Tulsa Public Birth through Eight Strategy for Tulsa (BEST) with Tulsa Public Birth through Eight Strategy for Tulsa (BEST) with Tulsa Public Birth through Eight Strategy for Tulsa (BEST) with Tulsa Public Birth through Eight Strategy for Tulsa (BEST) with Tulsa Public Birth through Eight Strategy for Tulsa (BEST) with Tulsa (BEST) with Tulsa Public Birth through Eight Strategy for Tulsa (BEST) with Tulsa (BEST) with Tulsa Public Birth through Eight Strategy for Tulsa (BEST) with Tulsa (BEST) with Tulsa (BEST) with Tulsa Public Birth through Eight Strategy for Tulsa (BEST) with Tulsa		TEE	Federated data model with joins and	Ongoing?
Type ure shing			TEE		
cure ashing	Oregon Departs	Yes	TEE	Character Lab, University of Pennet	Yes
ecure hashing	Families and even the second s	No	TEE	interaction interaction interaction interaction interaction	Yes
secure hashing	System		TEE	Secure virtual data enclave for research access to NCES Restricted Use Files	Yes
SMC	Boston University Boston Unive	Int Alle	ILE .	Secure virtual enclave for research	Yes
SMC	National Center for Education State			Children's Data on children Children's Data Network, University of Southern California Post-secondary Employment Outcomes (PSEO) Census Bureau, multiple post-sec. institutions	Yes
SMC	Virginia Longitudinal Data System Defense Advanced Virginia Longitudinal Data System Defense Advanced Virginia Longitudinal Data System Defense Advanced State Council of Higher Education for Virginia State Council of Higher Education for Virginia		T	RS, Statistics of Income Division	Yes

Conducted 40 stakeholder interviews to identify existing and abandoned projects



Most Common PETs

- Institutions were using:
 - Secure multiparty computation
 - Secure hashing
 - Secure enclave/trusted execution environment
 - Differential privacy
 - Synthetic data





Secure Multiparty Computation (SMC)

Secure multiparty computation (SMC): the process by which two distrusting parties jointly compute a research query on their datasets, without ever seeing the other's underlying data, through encryption.

✓ only aggregate results released	⊠ time-consuming
descriptive statistics	Iimited in operations/statistics
✓ finds overlap in datasets	requires careful data preparation
no trusted third party sees data	does not address output privacy

- Education examples: <u>Estonia</u>, <u>Virginia</u>, <u>our NCES demonstration</u>
- Other examples: <u>Boston Women's Workforce</u>, <u>Allegheny County Department of Human</u> <u>Services demonstration</u>, DARPA and IARPA investments



Differential Privacy (DP)

Differential privacy (DP): a method for obscuring identities or attributes in the underlying recordlevel data by infusing results/statistics with noise.

reduces re-identification risks for	challenging to implement on low levels
individuals or groups in the data (i.e.,	of geography or unique population
students, programs)	groups without adding a lot of noise
 provides a formal privacy guarantee (can guard against threats known today and those in the future) useful for known queries 	 tradeoff between privacy and accuracy – as you add more "noise" (protection) you move further from true values no input privacy

- Education examples: <u>U.S. Census Bureau's Post-Secondary Employment Outcomes</u>, <u>College Scorecard</u>
- Other examples: <u>Census 2020</u>, <u>Google</u>, <u>Apple</u>, <u>Facebook</u>



What Are Barriers to PET Deployment?

Legal

- Actual legal barriers
- Perceived/claimed legal barriers
- Data sharing agreements
- Not enough Yes lawyers

Institutional

- Politics/political cycle
- Protectionism
- Inertia/no demand for change
- No resources to test/implement
- Lack of expertise
- No guidance from feds

Technical

- Untested/unavailable tools
- Untrusted software
- No standards
- Slow compute
- Skills gap

Cultural

- Lack of PET understanding
- Lack of examples
- Lack of trust in service providers
- No incentive to change



Next Steps

- PET information and training sessions
- Develop guidance
- Field Building
- Demonstration projects
 - Synthetic data with Nebraska Statewide Workforce & Educational Reporting System
 - Secure query system with IRS
- In discussion: Secure enclave and multiparty computation with state ed. agencies





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Read our report, <u>**Privacy Preserving Technologies in Education**</u>





