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TEXAS
The University of Texas at Austin

GOOD SYSTEMS
A UT Grand Challenge

Towards Ethical Data Management, Distribution, and Use for Artificial Intelligence (AI) Applications

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Goals of the Research

- ➢ Investigate open data used in AI (artificial intelligence).
- ➢ Identify ethical tensions.

Key Questions

(1) What are key ethical data features from the perspectives of data producers, repositories and consumers?

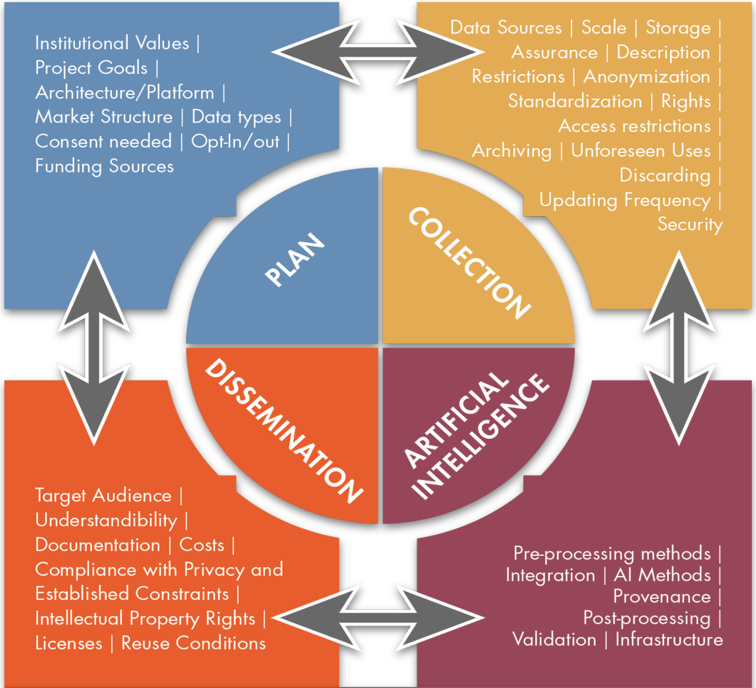
(2) How can ethical features, including the stakeholders' and data subjects' best interests, be effectively managed across the data lifecycle? What are the difficulties?

(3) What techniques can help identify and track ethical features in data?

Deliverables

- ➢ Actionable ethical data management framework
- ➢ Inform open repositories' policies towards ethical open data for use in responsible AI

The Start: AI Project and Data Lifecycle



Ethical data management as a point of departure in AI projects.

Data Use Case

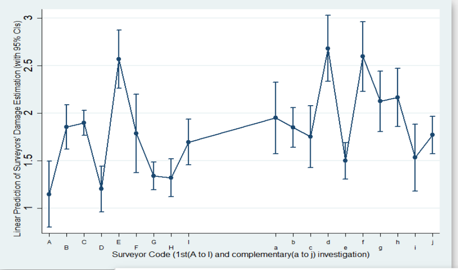
- ➢ Natural Hazards Engineering data.
- ➢ Ethical issues surrounding multiple stages of the data lifecycle
- ➢ Use of AI research methods is increasing in the space.

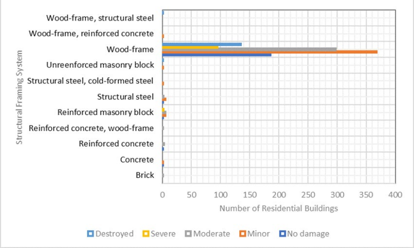
Hurricane Harvey doi:10.17603/DS2DX22

DESIGNSAFE-CI
NHERI: NATURAL HAZARDS ENGINEERING RESEARCH INFRASTRUCTURE

Data Assessment

- ➢ Unique aspects of Open Data
- ➢ Issues of completeness, access, diversity of variables, biases, inconsistencies, etc. E.g., are data appropriately fitted to train a ML model?





* (upper-bound) variance of ratings for Harvey-damaged buildings among coders; (lower-bound) distribution of building structure of Harvey-damaged buildings

* **Data used:** Roueche, David B.; Lombardo, Frank T.; Krupar III, Richard J.; Smith, Daniel J., (2018-08-22), "Collection of Perishable Data on Wind- and Surge-Induced Residential Building Damage During Hurricane Harvey (TX)" , DesignSafe-CI [publisher], Dataset, doi:10.17603/DS2DX22

Complementary views for understanding data

- ➢ Results offer a systemic but fragmented view of reality
- ➢ Lead to further relevant inquiries

- ➢ Bridge data and stakeholders with diverse research goals and positional interests

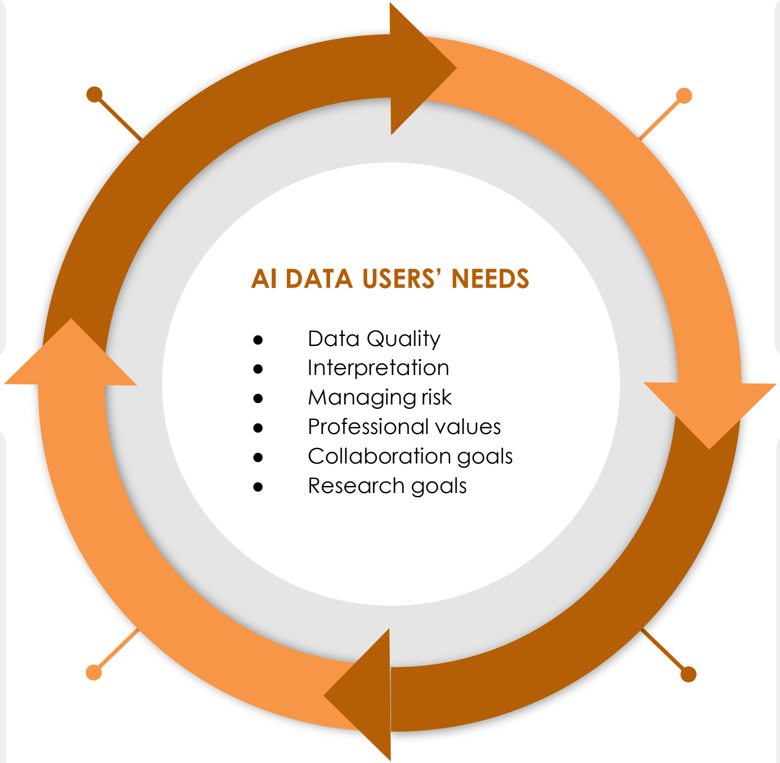
Methods: Interviews, Data Analysis and Observations

- ➢ Excavated Harvey datasets.
- ➢ Semi-structured interviews to data creators, repository managers, and system administrators.
  - ○ Data producers using different methods to collect/generate data.
  - ○ Pending interviews to data users.

Strategies and Benchmarks for Interpreting the Data

- ➢ Lifecycle of data.
- ➢ Research workflows with open data
- ➢ Tensions and values emerging from the interviews.
- ➢ Organizations, systems, and platforms.
- ➢ Who makes decisions? How?
- ➢ Policies and Practices.

Results as ethically charged themes



Data Creation/Gathering

- Costs of data
- Different perspectives and research goals
- Professional values
- Sensitivity towards affected community
- Sponsorship
- Not thinking about AI uses & needs

Data Processing

- Data quality
- Incentives
- Researchers' data quality responsibilities
- Research goals
- Sponsorship/ Costs
- Temporal issues

Data Storage

- Data quality /documentation
- Data security and Protection of PII
- Incentives
- Repository responsibilities
- Platform qualities
- Researchers' responsibilities
- Data sharing & longevity

Distributing and Communicating Data

- Access and discovery
- Audiences
- Data quality/ documentation
- Incentives
- Defining & Managing risk
- Understandability - Discovery
- Users responsibilities

Conclusions

Values

- Data quality (diversity, balance, completeness, documented, secure, no PII, etc.) is a fundamental ethical consideration.
- Data quality may be loose.
- Depending on research goals, methods and context, ethical concerns align more or less with those of the community affected and or providing the data.
- The community providing the data must be considered at all stages of the data lifecycle.
- Open access technologies and values may not be well understood by data creators.
- Data creators are not necessarily thinking about future data uses, including AI/ML.

Rewards

- Low incentives for data curation/publication in the academy.
- Demand for incentives.

Collaboration

- Compartmentalization of responsibilities and tasks between data creators, repositories, and users.
- Curation is not geared towards AI possibilities.
- Curation in the repository may be loose.
- Understandability may be difficult.
- Post-processing of data for AI use is done by the user.
- Repositories could be better brokers between the goals and values of the data creators and those of users.

Risks

- Risks of distributing data to decision makers - quick data gathering, uncertain quality, constraints on analysis.
- Risks of building AI models that are weak / biased / unbalanced