Expanding the reach of EHR through data integration

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Research Question

Integration of EHR data across institutes

- Electronic Health Record (EHR) data are playing an increasing role in generating realworld evidence (RWE) to support clinical decision making.
- Multi-site study using EHR data from clinical research networks is increasing popular due to larger sample size and broader population.
- Sharing individual patient data (IPD) across clinical sites is logistically challenging due to privacy concerns.
- Distributed algorithms for various models have been proposed in the literature, but most of them require iterative communications across sites.

Proposed Solution: PDA

- A toolbox of Privacy-preserving Distributed Algorithms that conduct distributed learning and inference for various models.
- Aims to facilitate efficient multi-institutional data analysis without sharing IPD.
- Compared to existing distributed algorithms, has the following features:
 - Accurate: provide estimates on par with the pooled estimator
 - Safe: only require aggregated data (AD)
 - Fast or NICE: Non-Iterative and Communication-Efficient
 - Heterogeneity-aware:handles betweensite heterogeneity
- PDA outperforms meta-analysis methods in many settings such as pharmacovigilance applications

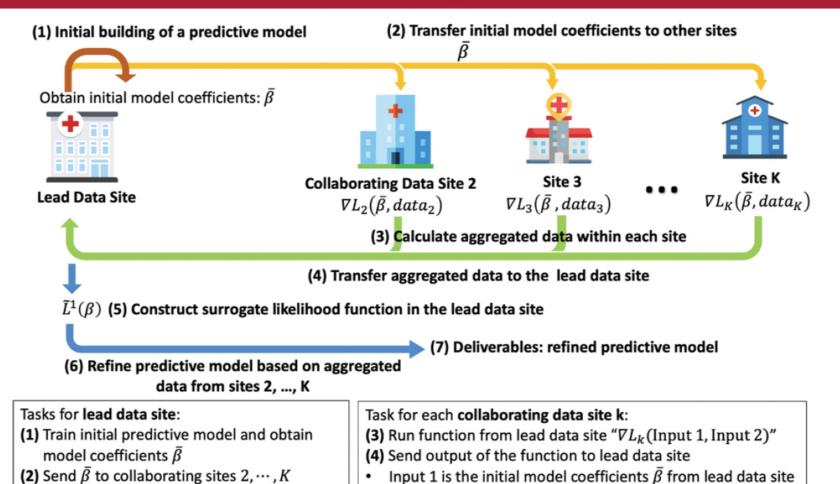
Funding







How PDA works



Availability of PDA

Input 2 is data from collaborating data site k

Output: a $p \times 1$ vector, rounded to the 2^{nd} decimal

(p is the # of predictors in the predictive model)

https://github.com/Penncil/pda



(5) Incorporate outputs (aggregated data) from

sites to refine initial predictive model

(6) Refine predictive model

pda

PDA: Privacy-preserving Distributed Algorithm ●C++ \$1 \$0 11 130

Specific Methods Developed & Validated

Binary outcomes:

- ODAL: One-shot Distributed Algorithm for Logistic Regression Model [Duan et al., 2019, 2020]
- ODAL-Robust, ODAL-H: One-shot Distributed Algorithm to Handle Heterogeneity across Clinical Sites [Tong et al. 2019; Tong et al.]

Continuous outcomes:

• ODALMM: One-shot Distributed Algorithm for Linear Mixed Model [Luo et al.]

Time-to-event outcomes:

• ODAC: One-shot Distributed Algorithm for Cox Proportional Hazards Model [Duan et al., 2020]

Count outcomes:

- ODAP: One-shot Distributed Algorithm for Poisson model [Edmondson et al.]
- ODAH: One-shot Distributed Algorithm to Handle Zero-inflated Counts using Hurdle Model [Edmondson et al.]

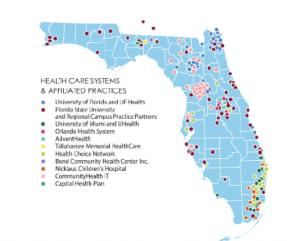
Use cases & Collaborations



OHDSI - drug adverse events



PEDSnet- pediatric Crohn's disease



OneFlorida – Alzheimer's disease/opioid use disorder

Selected Publications

- 1. Duan et al. ODAL: A one-shot distributed algorithm to perform logistic regressions on electronic health records data from multiple clinical sites. InPSB 2019.
- 2. Duan et al. Learning from electronic health records across multiple sites: A communication-efficient and privacy-preserving distributed algorithm. JAMIA 2020 Mar.
- 3. Duan et al. Learning from local to global: An efficient distributed algorithm for modeling time-to-event data. JAMIA 2020 July.
- 4. Tong et al. Robust-ODAL: Learning from heterogeneous health systems without sharing patient-level data. InPSB 2020