COMPUTATIONAL ALGORITHMS FOR DISTRIBUTED REGRESSION ANALYSIS BASED ON SAS SOFTWARE



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BACKGROUND & OBJECTIVES

Background:

- Distributed regression analysis (DRA) is a privacy-protecting analytic method that performs regression analysis with only summary-level data from participating sites (Figure 1)
- Feasibility and utility of DRA have been well documented [1]
- No DRA applications in SAS, the statistical software used by several national distributed data networks (DDNs), are available for routine use
- SAS/IML can be used to perform DRA computations, but not all data partners in national DDNs have access to SAS/IML, as it is licensed separately from SAS

Objective: To develop a DRA application using only BASE SAS and SAS/STAT modules for use in national DDNs

RESULTS

• The DRA SAS application produced regression parameter and standard error estimates within machine precision to the corresponding pooled patient-level data analyses produced by standard SAS procedures (Table 1)

CONCLUSION

- We successfully developed a DRA application using only SAS BASE and SAS/STAT modules
- The application may facilitate the adoption of DRA in national DDNs

REFERENCES

METHODS

We used a distributed iteratively reweighted least squares (IRLS) algorithm to perform distributed linear and logistic regression analysis and a distributed Newton-Raphson (NR) algorithm to perform distributed Cox proportional hazards regression analysis

- Algorithms were implemented using only BASE SAS and SAS/STAT modules
- The main steps in the algorithms include:
 - Compute summary data at each data partner (Figure 2)
 - Combine site-specific summary data at the analysis center
 - Execute PROC REG with SSCP-type input to solve the IRLS/NR system of equations
- A simulated horizontally partitioned DDN of three data partners and an analysis center was created to test the algorithms (Figure 3)
- PopMedNet, a secure distributed data sharing software, was used to transfer the summary data in the simulated DDN [1]

We used two different datasets to test the DRA application

- Distributed linear and logistic regression: "Boston Housing data," included 506 observations
 of medium housing prices and neighborhood characteristics [2]
- Data was randomly partitioned among data partners ($n_1 = 172$, $n_2 = 182$, $n_3 = 152$)
- Outcome: continuous housing price and dichotomized housing price (below or above median)
- o Covariates: crime, industrialization, and distance to employment centers
- **Distributed Cox proportional hazards regression:** "Maryland State Prison data," included 432 convicts followed for one year post release and baseline characteristics [3]

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Figure 2: Summary data example (linear regression)



- Data randomly partitioned among data partners ($n_1 = 134$, $n_2 = 149$, $n_3 = 149$)
- Outcome: time to re-incarceration (weeks)
- Covariates: financial aid, age, and number of prior convictions

Figure 1: Distributed regression analysis



Parameter estimates are distributed to the



Figure 3: Simulated distributed data network



Privacy is retained as patient-level data remains behind data partners' firewalls

data partners to fine tune the summary data

Table 1: Distributed Regression Analysis (DRA) vs. PooledPatient-Level Regression Analysis

Linear Regression (Boston Housing data)

	DF	RA	Pooled Pat	tient-Level	Difforences in	Differences in Standard Errors	
Covariates	Estimates	Standard	Ectimator	Standard	Differences in Decomposer Ectimator		
		Errors	Estimates	Errors	Parameter Estimates		
Intercept	35.50548	1.57690	35.50548	1.57690	-8.38E-13	2.26E-14	
Crime	-0.27283	0.04401	-0.27283	0.04401	4.44E-16	9.92E-16	
Distance	-1.01582	0.23259	-1.01582	0.23259	1.09E-13	3.22E-15	
Industry	-0.73017	0.07229	-0.73017	0.07229	3.54E-14	1.32E-15	

Logistic Regression (Boston Housing data)

Cox Proportional Hazards Regression (Maryland State Prison data)

	DF		Pooled Patient-Level		Differences in Differences in		DRA		Pooled Patient-Level		Difforences in	Difforences in	
Covariates	Standard		Standard		Differences in Decomptor Ectimator	Standard Errors	Covariates	Standard		Standar Ectimator		Differences in Deremeter Estimates	Standard Errors
	Estimates	Errors	Estimates	Errors	Parameter Estimates	Standard Errors		Estimates	Errors	Estimates	Parameter Estimates	Standard Errors	
Intercept	2.49660	0.49057	2.49660	0.49060	1.33E-15	9.99E-16							
Crime	-0.14465	0.03686	-0.14460	0.03690	2.04E-13	-2.97E-14	Age	-0.06692	0.02084	-0.06692	0.02084	-1.39E-16	2.78E-17
Distance	-0.14105	0.06976	-0.14100	0.06980	1.38E-14	-2.22E-16	Financial Aid	-0.34644	0.19024	-0.34644	0.19024	2.22E-16	-2.78E-17
Industry	-0.13889	0.02376	-0.13890	0.02380	2.42E-14	1.94E-09	Prior Arrest	0.09653	0.02724	0.09653	0.02724	-1.80E-16	1.73E-17

Data Partner 2