Cross-tissue eQTL mapping in the presence of missing data via surrogate outcome analysis

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Abstract

Missing data are prevalent in the Genotype-Tissue Expression (GTEx) project, where measurements from certain inaccessible tissues, such as the substantia nigra (SSN), are available at much smaller sample sizes than those from accessible tissues, such as blood. This severely limits power for identifying tissue-specific expression quantitative trait loci (eQTL). Here we propose Surrogate Phenotype Regression Analysis (Spray) for leveraging information from a correlated surrogate outcome (e.g. expression in blood) to improve inference on a partially missing target outcome (e.g. expression in SSN). Rather than regarding the surrogate outcome as a proxy for the target outcome, Spray jointly models the target and surrogate outcomes within a bivariate regression framework. Unobserved values of either outcome are regarded as missing data. We describe and implement an expectation conditional maximization algorithm for performing estimation in the presence of bilateral outcome missingness. We then demonstrate analytically, via the asymptotic relative efficiency, and empirically, through simulations and tissue-specific eQTL mapping, that in comparison with marginally modeling the target outcome, jointly modeling the target and surrogate outcomes increases estimation precision and improves power.

Keywords: Asymptotic Relative Efficiency; EM Algorithm; Genetic Association Analysis; Missing Data; Multivariate Analysis.

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1 Introduction

Tissue-specific expression quantitative trait loci (eQTL) are of substantial biological interest as mechanisms for explaining how the genetic variants identified in genome-wide association studies (GWAS) influence complex traits and diseases (Gamazon et al., 2015; Gusev et al., 2016; Hormozdiari et al., 2016; Zhu et al., 2016; Visscher et al., 2017). Traditional eQTL studies have focused on accessible tissues such as blood (Nica et al., 2011; Westra et al., 2013), while eQTL analyses in inaccessible tissues, such as brain, have been hindered by limited sample sizes. Cross-tissue studies, including the Genotype-Tissue Expression Project (GTEx), have demonstrated that the effect sizes of eQTL are heterogeneous across tissues (GTEx Consortium, 2017). Consequently, studying only accessible tissues is insufficient to understand the genetic basis of gene regulation. Larger sample sizes are needed to provide sufficient power for reliable eQTL detection in inaccessible tissues, and there is great interest in borrowing information from accessible tissues to boost the effective sample sizes in inaccessible tissues.

Our work on cross-tissue eQTL mapping was motivated by the goal of improving power for eQTL mapping in the substantia nigra (SSN). SSN is a region of the midbrain implicated in the development of Parkinson's disease (Poewe et al., 2017). Due to the scarcity of gene expression data from SSN, no previous studies have focused on eQTL mapping in this region. At the time of our study, only 73 genotyped subjects in GTEx had expression in SSN, whereas 369 genotyped subjects had expression in whole blood. Among subjects with expression in blood, 90% were missing expression in SSN. We were interested in leveraging expression from whole blood to empower eQTL mapping in SSN.

Existing remedies for eQTL mapping in the presence of missing data are *ad hoc*. Standard eQTL software adjusts for missingness using mean imputation or complete case analysis (Shabalin, 2012). Mean imputation, whether marginal or conditional on covariates, reduces outcome variability, leading to underestimated standard errors and invalid inference

(Little and Rubin, 2002). Complete case analysis can introduce bias when missingness is related to covariates, and makes inefficient use of the data even when the missingness occurs completely at random.

In this paper, we propose improving power for eQTL mapping in an inaccessible tissue (e.g. SSN), for which expression measurements are partially missing, by augmenting the sample with expression data from an accessible surrogate tissue (e.g. whole blood), for which the available sample size is substantially larger. Specifically, we propose jointly modeling expression in the target and surrogate tissues while regarding unobserved measurements in either tissue as missing data, an approach we describe as Surrogate Phenotype Regression Analysis (Spray). Spray leverages the correlation in expression levels across tissues to increase the effective sample size, but maintains eQTL in the target tissue as the focus of inference.

For estimation, we develop a computationally efficient Expectation Conditional Maximization Either (ECME) algorithm (Meng and Rubin, 1993; Liu and Rubin, 1994), which is adapted to fitting the association model in the presence of bilateral outcome missingness. The algorithm iterates between conditional maximization of the observed data log likelihood with respect to the regression parameters, and conditional maximization of the EM objective function with respect to the covariance parameters. In addition, we have derived the asymptotic covariance of all model parameters, and implemented a flexible Wald test for evaluating hypotheses about the target regression parameters in particular. We show analytically that the asymptotic efficiency of jointly modeling the target and surrogate outcomes, relative to marginally modeling the target outcome only, increases with the proportion of target outcomes missing and with the square of the target-surrogate correlation. We numerically demonstrate the analytical results through extensive simulations evaluating the empirical power of the Spray Wald test as a function of the target missingness and the target-surrogate correlation.

Compared to complete data analysis, maximum likelihood estimation as implemented

by SPRAY is efficient, makes full use of the available data, and provides unbiased estimates of the regression parameters, provided the missingness occurs at random. All estimation and inference procedures discussed in this article have been implemented in an easy-to-use `R` package (`SurrogateRegression`), which is available on CRAN (McCaw, 2020).

Using data from GTEx, we applied SPRAY to perform cross-tissue eQTL mapping, taking expression in SSN as the target outcome, and expression in whole blood as the surrogate outcome. Compared with marginal eQTL mapping based on expression in SSN only, SPRAY discovered 64.1% more significant eQTL at $\alpha = 5 \times 10^{-8}$. Importantly, while the effect sizes estimated by SPRAY were nearly identical to those obtained via marginal eQTL mapping ($R^2 = 0.998$), the sampling variance was reduced by 19.6%, on average, suggesting that SPRAY increased power primarily by drawing on the correlated surrogate outcome to improve precision. SPRAY identified 106 independent genomic loci not identified by the marginal analysis, each of which contained at least one previously reported GWAS variant. We highlight a variant on chromosome 1 (rs483259) that was associated with significantly decreased expression of the LRRIQ3 gene, and is in linkage disequilibrium (LD) with variants previously associated with increased educational attainment (Lee et al., 2018).

The remainder of this paper is organized as follows: Section 2 introduces the setting and model. Sections 3 and 4 detail the estimation and inference procedures. Section 5 addresses the estimand of SPRAY, and the asymptotic relative efficiency of jointly versus marginally modeling the target outcome. Section 6 presents the results of simulation studies, and section 7 the application to GTEx. We conclude with discussions in Section 8.

2 Model and Setting

For each of n independent subjects, suppose that two continuous outcomes are potentially observed: the *target outcome* T_i and the *surrogate outcome* S_i. Consider the model:

$$\begin{pmatrix} T_i \\ S_i \end{pmatrix} \Big| (\boldsymbol{x}_i, \boldsymbol{z}_i) \sim N \left\{ \begin{pmatrix} \boldsymbol{x}_i' & \mathbf{0} \\ \mathbf{0} & \boldsymbol{z}_i' \end{pmatrix} \begin{pmatrix} \boldsymbol{\beta} \\ \boldsymbol{\alpha} \end{pmatrix}, \begin{pmatrix} \Sigma_{TT} & \Sigma_{TS} \\ \Sigma_{ST} & \Sigma_{SS} \end{pmatrix} \right\}, \tag{1}$$

where $\boldsymbol{x}_i$ is a $p \times 1$ vector of covariates for the target outcome, with regression coefficient $\boldsymbol{\beta}$, and $\boldsymbol{z}_i$ is a $q \times 1$ vector of covariates for the surrogate outcome, with regression coefficient $\boldsymbol{\alpha}$. The 2×2 residual covariance matrix $\boldsymbol{\Sigma}$ is left unstructured. Let $\boldsymbol{y}_i = \text{vec}(T_i, S_i) \in \mathbb{R}^2$ denote the 2×1 outcome vector, $\mathcal{X}_i = \text{diag}(\boldsymbol{x}_i', \boldsymbol{z}_i')$ the $2 \times (p+q)$ subject-specific design matrix, and $\boldsymbol{\gamma} = \text{vec}(\boldsymbol{\beta}, \boldsymbol{\alpha})$ the $(p+q) \times 1$ overall regression coefficient, then model (1) is succinctly expressible as: $\boldsymbol{y}_i \big| \mathcal{X}_i \sim N\big(\mathcal{X}_i \boldsymbol{\gamma}, \boldsymbol{\Sigma}\big)$.

The target and surrogate outcomes are subject to arbitrary patterns of missingness at random (MAR). The MAR assumption ensures unbiased estimation of the regression parameters in model (1). Define the target $R_{T,i}$ and surrogate $R_{S,i}$ responses indicators:

$$R_{T,i} = \begin{cases} 1, & T_i \text{ is observed,} \\ 0, & T_i \text{ is missing.} \end{cases} \qquad R_{S,i} = \begin{cases} 1, & S_i \text{ is observed,} \\ 0, & S_i \text{ is missing.} \end{cases}$$

The response indicators partition the n subjects with at least one observed outcome into three distinct groups. For the first n_0 subjects, the target and surrogate outcomes are both observed: $(R_{T,i} = 1)$ and $(R_{S,i} = 1)$. These subjects are described as *complete cases*. For the next n_1 subjects, the target outcome is missing, while the surrogate outcome is observed: $(R_{T,i} = 0)$ and $(R_{S,i} = 1)$. These subjects are described as having *target missingness*. Among subjects with target missingness, the MAR assumption requires that $R_{T,i}$ is independent of T_i given the observed data, $(S_i, \boldsymbol{x}_i, \boldsymbol{z}_i)$. For the remaining n_2 subjects, the target outcome is observed, while the surrogate outcome is missing: $(R_{T,i} = 1)$ and $(R_{S,i} = 0)$. These

subjects are described as having *surrogate missingness*. Among subjects with surrogate missingness, the MAR assumption requires that $R_{S,i}$ is independent of S_i given the observed data, $(T_i, \boldsymbol{x}_i, \boldsymbol{z}_i)$. The n_1+n_2 subjects with either target or surrogate missingness are referred to collectively as *incomplete cases*.

3 Estimation

3.1 Regression Parameters

Define the response indicator matrix $\boldsymbol{R}_i = \text{diag}(R_{T,i}, R_{S,i})$, and note that $\boldsymbol{R}_i$ is a projection matrix. The distribution of the observed data is expressible as:

$$\boldsymbol{y}_i \big| (\boldsymbol{R}_i, \mathcal{X}_i) \sim N\big(\boldsymbol{R}_i \mathcal{X}_i \boldsymbol{\gamma}, \boldsymbol{R}_i \boldsymbol{\Sigma} \boldsymbol{R}_i\big),$$

and the observed data log likelihood is:

$$\begin{aligned} \ell_{\text{obs}}(\boldsymbol{\gamma}, \boldsymbol{\Sigma}) \propto & -\frac{1}{2}\sum_{i=1}^{n} \ln\det(\boldsymbol{R}_i \boldsymbol{\Sigma} \boldsymbol{R}_i) \\ & -\frac{1}{2}\sum_{i=1}^{n} (\boldsymbol{R}_i \boldsymbol{y}_i - \boldsymbol{R}_i \mathcal{X}_i \boldsymbol{\gamma})' (\boldsymbol{R}_i \boldsymbol{\Sigma} \boldsymbol{R}_i)^{-1} (\boldsymbol{R}_i \boldsymbol{y}_i - \boldsymbol{R}_i \mathcal{X}_i \boldsymbol{\gamma}). \end{aligned} \tag{2}$$

The observed data score equation for the regression parameters $\boldsymbol{\gamma}$ is:

$$\mathcal{U}_\gamma(\boldsymbol{\gamma}, \boldsymbol{\Sigma}) \equiv \frac{\partial \ell_{\text{obs}}}{\partial \boldsymbol{\gamma}} = \sum_{i=1}^{n} \mathcal{X}_i' \boldsymbol{R}_i' (\boldsymbol{R}_i \boldsymbol{\Sigma} \boldsymbol{R}_i)^{-1} (\boldsymbol{R}_i \boldsymbol{y}_i - \boldsymbol{R}_i \mathcal{X}_i \boldsymbol{\gamma}).$$

Conditional on $\boldsymbol{\Sigma}$, the maximum likelihood estimator (MLE) of $\boldsymbol{\gamma}$ is the generalized least squares (GLS) estimator:

$$\hat{\boldsymbol{\gamma}}(\boldsymbol{\Sigma}) = \left\{ \sum_{i=1}^{n} \mathcal{X}_i' \boldsymbol{R}_i' (\boldsymbol{R}_i \boldsymbol{\Sigma} \boldsymbol{R}_i)^{-1} \boldsymbol{R}_i \mathcal{X}_i \right\}^{-1} \left\{ \sum_{i=1}^{n} \mathcal{X}_i' \boldsymbol{R}_i' (\boldsymbol{R}_i \boldsymbol{\Sigma} \boldsymbol{R}_i)^{-1} \boldsymbol{y}_i \right\}. \tag{3}$$

3.2 Covariance Matrix

Let $\boldsymbol{\epsilon}_i = (\boldsymbol{y}_i - \mathcal{X}_i\boldsymbol{\gamma})$ denote the residual vector. The observed data score equation for $\boldsymbol{\Sigma}$ is:

$$\mathcal{U}_\Sigma(\boldsymbol{\gamma}, \boldsymbol{\Sigma}) \equiv \frac{\partial \ell_{\text{obs}}}{\partial \boldsymbol{\Sigma}} = -\frac{1}{2}\sum_{i=1}^{n} \boldsymbol{R}_i(\boldsymbol{R}_i\boldsymbol{\Sigma}\boldsymbol{R}_i)^{-1}\boldsymbol{R}_i + \frac{1}{2}\sum_{i=1}^{n} \boldsymbol{R}_i(\boldsymbol{R}_i\boldsymbol{\Sigma}\boldsymbol{R}_i)^{-1}\boldsymbol{\epsilon}_i\boldsymbol{\epsilon}_i'(\boldsymbol{R}_i\boldsymbol{\Sigma}\boldsymbol{R}_i)^{-1}\boldsymbol{R}_i.$$

However, the score equation for $\boldsymbol{\Sigma}$ does not admit a closed form. To obtain the MLE, we apply the ECME algorithm (Meng and Rubin, 1993; Liu and Rubin, 1994). Define the 2×2 *residual outer product* matrix:

$$\boldsymbol{V}_i \equiv \boldsymbol{\epsilon}_i \otimes \boldsymbol{\epsilon}_i = \begin{pmatrix} (T_i - \boldsymbol{x}_i'\boldsymbol{\beta})^2 & (T_i - \boldsymbol{x}_i'\boldsymbol{\beta})(S_i - \boldsymbol{z}_i'\boldsymbol{\alpha}) \\ (S_i - \boldsymbol{z}_i'\boldsymbol{\alpha})(T_i - \boldsymbol{x}_i'\boldsymbol{\beta}) & (S_i - \boldsymbol{z}_i'\boldsymbol{\alpha})^2 \end{pmatrix}.$$

The *complete data log likelihood* is now expressible as:

$$\ell(\boldsymbol{\gamma}, \boldsymbol{\Sigma}) \propto -\frac{n}{2}\ln\det(\boldsymbol{\Sigma}) - \frac{1}{2}\text{tr}\left(\boldsymbol{\Sigma}^{-1}\sum_{i=1}^{n}\boldsymbol{V}_i\right). \tag{4}$$

The *EM objective* is the expectation of the complete data log likelihood in (4) given the observed data $\mathcal{D}_{\text{obs}}$ and the current parameter estimates $(\boldsymbol{\gamma}^{(r)}, \boldsymbol{\Sigma}^{(r)})$:

$$Q(\boldsymbol{\gamma}, \boldsymbol{\Sigma}|\boldsymbol{\gamma}^{(r)}, \boldsymbol{\Sigma}^{(r)}) \equiv E\big\{\ell(\boldsymbol{\gamma}, \boldsymbol{\Sigma})|\mathcal{D}_{\text{obs}}; \boldsymbol{\gamma}^{(r)}, \boldsymbol{\Sigma}^{(r)}\big\}. \tag{5}$$

To obtain an expression for (5), define the *working outcome vector*:

$$\hat{\boldsymbol{y}}_i^{(r)} \equiv E\big(\boldsymbol{y}_i|\mathcal{D}_{\text{obs}}; \boldsymbol{\gamma}^{(r)}, \boldsymbol{\Sigma}^{(r)}\big) = \begin{cases} (T_i, S_i)', & (R_{T,i} = 1) \wedge (R_{S,i} = 1), \\ (\hat{T}_i^{(r)}, S_i)', & (R_{T,i} = 0) \wedge (R_{S,i} = 1), \\ (T_i, \hat{S}_i^{(r)})', & (R_{T,i} = 1) \wedge (R_{S,i} = 0). \end{cases}$$

For complete cases, the working outcome vector is identically the observed outcome vector. For subjects with target missingness, the unobserved value of T_i is replaced by its conditional

expectation given the surrogate outcome and covariates:

$$\hat{T}_i^{(r)} \equiv E(T_i|S_i, \mathcal{X}_i; \boldsymbol{\gamma}^{(r)}, \boldsymbol{\Sigma}^{(r)}) = \boldsymbol{x}_i'\boldsymbol{\beta}^{(r)} + \left(\Sigma_{TS}\Sigma_{SS}^{-1}\right)^{(r)}\left(T_i - \boldsymbol{z}_i'\boldsymbol{\alpha}^{(r)}\right).$$

Similarly, for subjects with surrogate missingness, the unobserved value of S_i is replaced by its conditional expectation give the target outcome and covariates:

$$\hat{S}_i^{(r)} \equiv E(S_i|T_i, \mathcal{X}_i; \boldsymbol{\gamma}^{(r)}, \boldsymbol{\Sigma}^{(r)}) = \boldsymbol{z}_i'\boldsymbol{\alpha}^{(r)} + \left(\Sigma_{ST}\Sigma_{TT}^{-1}\right)^{(r)}(T_i - \boldsymbol{x}_i'\boldsymbol{\beta}^{(r)}).$$

Let $\boldsymbol{\Lambda} = \boldsymbol{\Sigma}^{-1}$ denote the precision matrix. Define the *working residual outer product*:

$$\begin{aligned}
\hat{\boldsymbol{V}}_i^{(r)} &\equiv E(\boldsymbol{V}_i|\mathcal{D}_{\text{obs}}; \boldsymbol{\gamma}^{(r)}, \boldsymbol{\Sigma}^{(r)}) \\
&= \left(\hat{\boldsymbol{y}}_i^{(r)} - \mathcal{X}_i\boldsymbol{\gamma}\right) \otimes \left(\hat{\boldsymbol{y}}_i^{(r)} - \mathcal{X}_i\boldsymbol{\gamma}\right) + \begin{cases} \text{diag}(0,0), & (R_{T,i} = 1) \wedge (R_{S,i} = 1), \\ \text{diag}\left(\Lambda_{TT}^{-1,(r)}, 0\right), & (R_{T,i} = 0) \wedge (R_{S,i} = 1), \\ \text{diag}\left(0, \Lambda_{SS}^{-1,(r)}\right), & (R_{T,i} = 1) \wedge (R_{S,i} = 0). \end{cases}
\end{aligned}$$

Note that $\hat{\boldsymbol{V}}_i^{(r)} = \hat{\boldsymbol{V}}_i(\boldsymbol{\gamma}|\boldsymbol{\gamma}^{(r)}, \boldsymbol{\Sigma}^{(r)})$ is a function of the true regression coefficient $\boldsymbol{\gamma}$, and of the current parameter estimates $(\boldsymbol{\gamma}^{(r)}, \boldsymbol{\Sigma}^{(r)})$. Expressed in terms of the working residual outer product, the EM objective function is:

$$Q(\boldsymbol{\gamma}, \boldsymbol{\Sigma}|\boldsymbol{\gamma}^{(r)}, \boldsymbol{\Sigma}^{(r)}) = -\frac{n}{2}\ln\det(\boldsymbol{\Sigma}) - \frac{1}{2}\text{tr}\left(\boldsymbol{\Sigma}^{-1}\sum_{i=1}^{n}\hat{\boldsymbol{V}}_i^{(r)}\right).$$

The EM score equation for $\boldsymbol{\Sigma}$ is:

$$\mathcal{U}_\Sigma(\boldsymbol{\gamma}, \boldsymbol{\Sigma}|\boldsymbol{\gamma}^{(r)}, \boldsymbol{\Sigma}^{(r)}) \equiv \frac{\partial Q}{\partial \boldsymbol{\Sigma}} = -\frac{n}{2}\boldsymbol{\Sigma}^{-1} + \frac{1}{2}\boldsymbol{\Sigma}^{-1}\left(\sum_{i=1}^{n}\hat{\boldsymbol{V}}_i^{(r)}\right)\boldsymbol{\Sigma}^{-1}.$$

Conditional on $\boldsymbol{\gamma}$, the EM update for $\boldsymbol{\Sigma}$ is:

$$\hat{\boldsymbol{\Sigma}}^{(r+1)}(\boldsymbol{\gamma}) \leftarrow \frac{1}{n}\sum_{i=1}^{n} \hat{\boldsymbol{V}}_i(\boldsymbol{\gamma}|\boldsymbol{\gamma}^{(r)}, \boldsymbol{\Sigma}^{(r)}). \tag{6}$$

3.3 Optimization

We propose the following ECME algorithm, in which the regression parameters $\boldsymbol{\gamma}$ are updated via conditional maximization of the observed data log likelihood in (2), and the covariance matrix $\boldsymbol{\Sigma}$ is updated via conditional maximization of the EM objective in (5).

Algorithm 1 ECME for Bivariate Normal Regression

Require: For each subject, observed response and covariate data $(\boldsymbol{R}_i\boldsymbol{y}_i, \mathcal{X}_i)$.
Require: Initial estimates of the regression $\boldsymbol{\gamma}^{(0)}$ and covariance $\boldsymbol{\Sigma}^{(0)}$ parameters.

```
repeat
    GLS step: Update γ^(r+1) ← γ̂(Σ^(r)) via (3).
    ECM step: Update Σ^(r+1) ← Σ̂(γ^(r+1)) via (6).
    Update observed data log likelihood ℓ_obs^(r+1) ← ℓ_obs(γ^(r+1), Σ^(r+1)) via (2).
until ℓ_obs^(r+1) − ℓ_obs^(r) < ε, where ε is the tolerance.
return Final estimates of the regression γ̂ and covariance Σ̂ parameters.
```

The accompanying `R` package initializes $\boldsymbol{\gamma}$ via ordinary least squares using all observed data:

$$\boldsymbol{\gamma}^{(0)} = \left\{\sum_{i=1}^{n} \mathcal{X}_i'\boldsymbol{R}_i\mathcal{X}_i\right\}^{-1}\left\{\sum_{i=1}^{n} \mathcal{X}_i'\boldsymbol{R}_i\boldsymbol{y}_i\right\}.$$

Given $\boldsymbol{\gamma}^{(0)}$, $\boldsymbol{\Sigma}$ is initialized using the residual outer product of the n_0 complete cases:

$$\boldsymbol{\Sigma}^{(0)} = \frac{1}{n_0}\sum_{i=1}^{n_0}(\boldsymbol{y}_i - \mathcal{X}_i\boldsymbol{\gamma}^{(0)}) \otimes (\boldsymbol{y}_i - \mathcal{X}_i\boldsymbol{\gamma}^{(0)}).$$

4 Inference

The ECME algorithm presented in the previous section does immediately provide the asymptotic information of the MLEs. The observed-data information matrices were ob-

tained using the following identity:

$$\mathrm{Var}\Big[E\big\{\mathcal{U}(\boldsymbol{\theta})|\mathcal{D}_{\mathrm{obs}}\big\}\Big] = \mathrm{Var}\big\{\mathcal{U}(\boldsymbol{\theta})\big\} - E\Big[\mathrm{Var}\big\{\mathcal{U}(\boldsymbol{\theta})|\mathcal{D}_{\mathrm{obs}}\big\}\Big],$$

where $\mathcal{U}(\boldsymbol{\theta})$ is the complete-data score, and $\mathcal{D}_{\mathrm{obs}}$ is the observed data. The observed-data information for the regression parameters $\boldsymbol{\gamma}$ decomposes as:

$$\mathcal{I}_{\gamma\gamma'} \equiv \begin{pmatrix} \mathcal{I}_{\beta\beta'} & \mathcal{I}_{\beta\alpha'} \\ \mathcal{I}_{\alpha\beta'} & \mathcal{I}_{\alpha\alpha'} \end{pmatrix} = \mathcal{I}_{\gamma\gamma',0} + \mathcal{I}_{\gamma\gamma',1} + \mathcal{I}_{\gamma\gamma',2}. \tag{7}$$

$\mathcal{I}_{\gamma\gamma',0}$ is the contribution of complete cases and takes the form:

$$\mathcal{I}_{\gamma\gamma',0} = \sum_{i_0=1}^{n_0} \begin{pmatrix} \boldsymbol{x}_{i_0}'\Lambda_{TT}\boldsymbol{x}_{i_0} & \boldsymbol{x}_{i_0}'\Lambda_{TS}\boldsymbol{z}_{i_0} \\ \boldsymbol{z}_{i_0}'\Lambda_{ST}\boldsymbol{x}_{i_0} & \boldsymbol{z}_{i_0}'\Lambda_{SS}\boldsymbol{z}_{i_0} \end{pmatrix}.$$

$\mathcal{I}_{\gamma\gamma',1}$ is the contribution of subjects with target missingness and $\mathcal{I}_{\gamma\gamma',2}$ is the contribution of subjects with surrogate missingness; these take the following forms respectively:

$$\mathcal{I}_{\gamma\gamma',1} = \sum_{i_1=1}^{n_1} \begin{pmatrix} 0 & 0 \\ 0 & \boldsymbol{z}_{i_1}'\Sigma_{SS}^{-1}\boldsymbol{z}_{i_1} \end{pmatrix}, \qquad \mathcal{I}_{\gamma\gamma',2} = \sum_{i_2=1}^{n_2} \begin{pmatrix} \boldsymbol{x}_{i_2}'\Sigma_{TT}^{-1}\boldsymbol{x}_{i_2} & 0 \\ 0 & 0 \end{pmatrix}.$$

Complete cases contribute to the information for all regression parameters, subjects with target missingness contribute to the information for the surrogate regression parameters $\boldsymbol{\alpha}$ only, and subjects with surrogate missingness contribute to the information for the target regression parameters $\boldsymbol{\beta}$ only.

Let $\varsigma = \mathrm{vec}(\Sigma_{TT}, \Sigma_{TS}, \Sigma_{SS})$ vectorize the covariance parameters. The observed-data

information for $\boldsymbol{\varsigma}$ likewise decomposes as:

$$\mathcal{I}_{\varsigma\varsigma'} = \begin{pmatrix} \mathcal{I}_{\varsigma_1\varsigma_1} & \mathcal{I}_{\varsigma_1\varsigma_2} & \mathcal{I}_{\varsigma_1\varsigma_3} \\ \mathcal{I}_{\varsigma_2\varsigma_1} & \mathcal{I}_{\varsigma_2\varsigma_2} & \mathcal{I}_{\varsigma_2\varsigma_3} \\ \mathcal{I}_{\varsigma_3\varsigma_1} & \mathcal{I}_{\varsigma_3\varsigma_2} & \mathcal{I}_{\varsigma_3\varsigma_3} \end{pmatrix} = \mathcal{I}_{\varsigma\varsigma',0} + \mathcal{I}_{\varsigma\varsigma',1} + \mathcal{I}_{\varsigma\varsigma',2}. \tag{8}$$

$\mathcal{I}_{\varsigma\varsigma',0}$ is the contribution of complete cases:

$$\mathcal{I}_{\varsigma\varsigma',0} = \frac{n_0}{2} \begin{pmatrix} \Lambda_{TT}^2 & 2\Lambda_{TT}\Lambda_{TS} & \Lambda_{TS}^2 \\ 2\Lambda_{TT}\Lambda_{TS} & 2\Lambda_{TS}^2 + 2\Lambda_{TT}\Lambda_{SS} & 2\Lambda_{TS}\Lambda_{SS} \\ \Lambda_{TS}^2 & 2\Lambda_{TS}\Lambda_{SS} & \Lambda_{SS}^2 \end{pmatrix}.$$

$\mathcal{I}_{\varsigma\varsigma',1}$ is the contribution of subjects with target missingness and $\mathcal{I}_{\varsigma\varsigma',1}$ is the contribution of subjects with surrogate missingness; they take the following forms respectively:

$$\mathcal{I}_{\varsigma\varsigma',1} = \frac{n_1}{2} \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \Sigma_{SS}^{-2} \end{pmatrix}, \quad \mathcal{I}_{\varsigma\varsigma',2} = \frac{n_2}{2} \begin{pmatrix} \Sigma_{TT}^{-2} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}.$$

Similarly, complete cases contribution to the information for all covariance parameters, subjects with target missingness contribute to the information on the surrogate variance only, and subjects with surrogate missingness contribute to the information for the target variance only.

The cross information $\mathcal{I}_{\gamma\varsigma'}$ between the regression $\boldsymbol{\gamma}$ and covariance $\boldsymbol{\varsigma}$ parameters is zero. Thus, the MLEs $\hat{\boldsymbol{\gamma}}$ and $\hat{\boldsymbol{\Sigma}}$ are asymptotically independent. For eQTL mapping, inference on the target regression parameter $\boldsymbol{\beta} \subseteq \boldsymbol{\gamma}$ is performed using the standard Wald test, the details of which are presented in the supplemental material.

5 Analytical Considerations

5.1 Marginal Interpretation of the Regression Parameter

The choice to jointly model S_i and T_i, rather than conditioning on S_i to predict T_i, has important implications when interpreting the association coefficients estimated by SPRAY. For exposition, suppose (1) is the generative model, and consider the setting where the target and surrogate means each depend on genotype g_i only:

$$\begin{pmatrix} T_i \\ S_i \end{pmatrix} \Big| g_i \sim N \left\{ \begin{pmatrix} g_i \beta_G \\ g_i \alpha_G \end{pmatrix}, \begin{pmatrix} \Sigma_{TT} & \Sigma_{TS} \\ \Sigma_{ST} & \Sigma_{SS} \end{pmatrix} \right\}. \tag{9}$$

The implied marginal distribution of the target outcome from (9) is:

$$T_i | g_i \sim N(g_i \beta_G, \Sigma_{TT}). \tag{10}$$

Thus, the regression parameter β_G for genotype in the joint model is identical to the regression parameter for genotype in the marginal model, and this equality is unchanged by the presence or absence of an association α_G between genotype g_i the surrogate outcome S_i. Importantly, as is confirmed by our simulation studies, this implies that inference on β_G under the joint model (1) does not depend on the value of α_G. The same is not true of a model that conditions on the surrogate outcome, for conditional on the surrogate outcome, the target outcome is distributed as:

$$T_i | (S_i, g_i) \sim N\big\{ (\beta_G - \Sigma_{TS}\Sigma_{SS}^{-1}\alpha_G) g_i + \Sigma_{TS}\Sigma_{SS}^{-1} S_i, \Sigma_{TT} - \Sigma_{TS}\Sigma_{SS}^{-1}\Sigma_{ST} \big\}.$$

Suppose that the target and surrogate outcomes are associated ($\Sigma_{TS} \neq 0$), which is a prerequisite for modeling the surrogate outcome to improve inference on β_G. Then, in a model that regresses T_i on both (S_i, g_i), the magnitude and direction of the regression coefficient

for genotype, namely $(\beta_G - \Sigma_{TS}\Sigma_{SS}^{-1}\alpha_G)$, depends on whether genotype is associated with the surrogate outcome ($\alpha_G \neq 0$).

5.2 Efficiency Analysis

Consider again the genotype only model in (9). Suppose initially that all subjects are complete cases, and that the genotypes have been scaled such that: $\sum_{i_0=1}^{n_0} g_{i_0}^2 = n_0$. Under these assumptions, the *efficient information* for β_G from (9) is:

$$\mathcal{I}_{\beta_G\beta_G|\alpha_G} = n_0\big(\Lambda_{TT} - \Lambda_{TS}\Lambda_{SS}^{-1}\Lambda_{ST}\big) = n_0\Sigma_{TT}^{-1}.$$

This is identical to the information for β_G from the marginal model in (10). Thus, in the absence of missingness, inference on β_G under the joint model (9) is asymptotically equivalent to inference on β_G under the marginal model (10).

Now suppose there are n_0 complete cases and n_1 subjects with target missingness. For simplicity, assume no subjects have surrogate missingness, $n_2 = 0$. Genotypes have again been scaled, within outcome missingness strata, such that among complete cases $\sum_{i_0=1}^{n_0} g_{i_0}^2 = n_0$; and among subjects with target missingness $\sum_{i_1=1}^{n_1} g_{i_1}^2 = n_1$. The efficient information from (9) becomes:

$$\mathcal{I}_{\beta_G\beta_G|\alpha_G} = n_0\left\{\Lambda_{TT} - \Lambda_{TS}\frac{n_0}{\big(n_0\Lambda_{SS} + n_1\Sigma_{SS}^{-1}\big)}\Lambda_{ST}\right\},$$

while the information for β_G based on the marginal model remains $\mathcal{I}_{\beta_G\beta_G} = n_0\Sigma_{TT}^{-1}$. The *asymptotic relative efficiency* (ARE) of inference under the joint model (9) compared to inference under marginal model (10) is:

$$\text{ARE} = \frac{\mathcal{I}_{\beta_G\beta_G|\alpha_G}}{\mathcal{I}_{\beta_G\beta_G}} = \Sigma_{TT}\left\{\Lambda_{TT} - \Lambda_{TS}\frac{n_0}{\big(n_0\Lambda_{SS} + n_1\Sigma_{SS}^{-1}\big)}\Lambda_{ST}\right\}. \tag{11}$$

To better understand (11), suppose the covariance matrix in (9) is a correlation matrix,

with $\Sigma_{TT} = \Sigma_{SS} = 1$, and correlation $\Sigma_{TS} = \rho \in (-1, 1)$. The ARE becomes:

$$\text{ARE} = \frac{1}{1-\rho^2}\left\{1 - \frac{\rho^2}{1-\rho^2} \cdot \frac{n_0}{n_0(1-\rho^2)^{-1} + n_1}\right\} = \frac{1}{1-\pi_T\rho^2},$$

where $\pi_T = n_1/(n_0 + n_1)$ is the proportion of subjects with target missingness. Now, if the target and surrogate outcomes are uncorrelated ($\rho = 0$), or if there is no target missingness ($\pi_T = 0$), then the ARE is 1, and inference based on the marginal model is asymptotically equivalent to inference based on the joint model. For fixed target missingness π_T, the ARE increases monotonically in the squared target-surrogate correlation ρ^2. In the limit as $\rho \to 1$, the ARE is maximized at $(1 - \pi_T)^{-1} = 1 + n_1/n_0$. Likewise, for fixed target-surrogate correlation ρ^2, the ARE increases monotonically in the target missingness π_T. In the limit as $\pi_T \to 1$, which occurs when $n_1 \to \infty$, the ARE is maximized at $(1 - \rho^2)^{-1}$. Overall, the power gain attributable to jointly modeling the target and surrogate outcomes is expected to increase with the squared target-surrogate correlation ρ^2, and with the number of subjects with target missingness n_1. This demonstrates theoretically that, by leveraging the correlation between the target and surrogate outcomes, inference on the target outcome can be improved by incorporating information from subjects with target missingness.

6 Simulation Studies

6.1 Simulation Methods

Additively coded genotypes $g_i \in \{0, 1, 2\}$ were drawn from a binomial distribution with minor allele frequency of 25%. Covariates included age and sex: age was drawn from a gamma distribution with mean 50 and variance 10; sex was drawn from a Bernoulli distribution with proportion 1/2. To emulate population structure, the top 3 PCs of the empirical genetic relatedness matrix (GRM) were included as covariates. For all simulations, the target $\mu_{T,i}$ and surrogate $\mu_{S,i}$ regressions each included an intercept, age, sex, and three

genetic PCs. Fixed effect regression coefficients were selected such that the proportion of total outcome-variation explained (PVE) by age and sex was 20%, and the PVE by genetic PCs was 5%. Initially, all simulations were performed in the presence ($\alpha_G \neq 0$) and absence ($\alpha_G = 0$) of an effect for genotype on the *surrogate* outcome. However, since α_G had no effect on the operating characteristics of SPRAY, including both size and power, only results for $\alpha_G = 0$ are reported here. For size simulations, genotype had no effect on the target outcome ($\beta_G = 0$). For power simulations, the effect of genotype was varied to achieve heritabilities between 0.1 and 1.0% ($\beta_G = 1/\sqrt{749}$ to $\beta_G = 1/\sqrt{74}$). Given genotype g_i and covariates $\boldsymbol{x}_i$, the target T_i and surrogate S_i outcomes were generated from the model:

$$\begin{pmatrix} T_i \\ S_i \end{pmatrix} \big| (g_i, \boldsymbol{x}_i) \sim N \left\{ \begin{pmatrix} g_i \beta_G + \boldsymbol{x}_i' \boldsymbol{\beta}_X \\ g_i \alpha_G + \boldsymbol{x}_i' \boldsymbol{\alpha}_X \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right\}.$$

The number of complete cases was fixed at $n_0 = 10^3$, while the numbers of subjects with target n_1 and with surrogate missingness n_2 were varied to achieve the specified levels of target $\pi_T = n_1/(n_0 + n_1 + n_2)$ and surrogate $\pi_S = n_2/(n_0 + n_1 + n_2)$ missingness. For example, when $\pi_T = 0.25$ and $\pi_S = 0.25$, the strata sizes were $n_0 = 10^3$ complete cases, $n_1 = 500$ subjects with target missingness, and $n_2 = 500$ subjects with surrogate missingness. Seven (target, surrogate) missingness patterns (π_T, π_S) were considered: no missingness $(0.00, 0.00)$; unilateral target missingness $\{(0.25, 0.00), (0.50, 0.00), (0.75, 0.00)\}$; and bilateral outcome missingness $\{(0.25, 0.25), (0.50, 0.25), (0.25, 0.50)\}$. For each missingness pattern, the target-surrogate correlation ρ spanned $\{0.00, 0.25, 0.50, 0.75\}$.

6.2 Estimation

Estimation simulations were conducted to evaluate the finite sample performance of SPRAY for estimating the model parameters and calibration of the model-based standard errors (SEs). Table 1 considers estimation of the target genetic effect β_G, the target variance Σ_{TT},

and the target-surrogate correlation ρ in the absence of missingness, and in the presence of unilateral missingness in the target outcome. The true genetic effect size $\beta_G \approx 0.08$ was selected such that the heritability was 0.5%. The true target variance was $\Sigma_{TT} = 1.00$. The surrogate missingness was fixed at $\pi_S = 0.00$, while the target missing π_T and target-surrogate correlation ρ were varied. The point estimate is the average across $R = 5 \times 10^7$. SEs are presented as the root mean square model-based SE, accompanied by the empirical standard deviation of point estimates across simulation replicates. In all cases, parameter estimation was essentially unbiased, and the model-based SEs, obtained from (7), agreed closely with the empirical standard deviations of the point estimates. Analogous tables for estimation of $(\beta_G, \Sigma_{TT}, \rho)$ in the presence of bilateral missingness (S1), and for estimation of (α_G, Σ_{SS}) both unilateral and bilateral missingness (S2) are presented in the supplementary materials.

6.3 Type I Error Simulations

Type I error simulations were conducted to assess the validity of the SPRAY Wald test. Table 2 presents the empirical type I error for assessing the $H_0 : \beta_G = 0$ in the presence of unilateral missingness, and type I error estimates in the presence of bilateral missingness are presented in supplementary table S3. For these simulations the genetic effects were set to zero ($\beta_G = \alpha_G = 0.00$). The type I error was controlled near the nominal level, and was insensitive to either outcome missingness or target-surrogate correlation.

Supplemental figures S1-S2 demonstrate that, across outcome missingness patterns and target-surrogate correlation levels, the p-values provided by the SPRAY Wald test were uniformly distributed under the null. Thus, SPRAY provides a valid test of association between genotype and the target outcome. Neither the type I error estimates nor the distribution of p-values were affected by the presence ($\alpha_G \neq 0$) or absence ($\alpha_G = 0$) of a genetic effect on the surrogate outcome.

Table 1: **Target parameter estimation and standard error calibration across $R = 5 \times 10^7$ simulations in the presence of unilateral missingness**. The number of complete cases was $n_0 = 10^3$. The true regression coefficient ($\beta_G \approx 0.08$) was chosen such that the heritability of the target outcome was 0.5%. The true variances of the target and surrogate outcomes were $\Sigma_{TT} = \Sigma_{SS} = 1.00$. The surrogate missingness was fixed at $\pi_S = 0.00$. The target missingness π_T and target-surrogate correlation ρ were varied. The point estimate (EST) is the average across simulation replicates. The standard error is presented as the root mean square model-based standard error (SE_M), followed by the empirical standard error (SE_E) in parentheses, which is the standard deviation across the point estimates of simulation replicates.

Settings		$\boldsymbol{\beta_G}$		$\boldsymbol{\Sigma_{TT}}$		$\boldsymbol{\rho}$	
ρ	π_T	EST	SE_M (SE_E)	EST	SE_M (SE_E)	EST	SE_M (SE_E)
0.00	0.00	0.08	0.05 (0.05)	0.99	0.04 (0.04)	0.00	0.03 (0.03)
0.25	0.00	0.08	0.05 (0.05)	0.99	0.04 (0.04)	0.25	0.03 (0.03)
0.50	0.00	0.08	0.05 (0.05)	0.99	0.04 (0.04)	0.50	0.04 (0.04)
0.75	0.00	0.08	0.05 (0.05)	0.99	0.04 (0.05)	0.75	0.04 (0.04)
0.00	0.25	0.08	0.05 (0.05)	0.99	0.04 (0.04)	0.00	0.03 (0.03)
0.25	0.25	0.08	0.05 (0.05)	0.99	0.04 (0.04)	0.25	0.03 (0.03)
0.50	0.25	0.08	0.05 (0.05)	0.99	0.04 (0.04)	0.50	0.03 (0.03)
0.75	0.25	0.08	0.05 (0.05)	0.99	0.04 (0.04)	0.75	0.04 (0.04)
0.00	0.50	0.08	0.05 (0.05)	0.99	0.04 (0.04)	0.00	0.03 (0.03)
0.25	0.50	0.08	0.05 (0.05)	0.99	0.04 (0.04)	0.25	0.03 (0.03)
0.50	0.50	0.08	0.05 (0.05)	1.00	0.04 (0.04)	0.50	0.03 (0.03)
0.75	0.50	0.08	0.04 (0.04)	1.00	0.04 (0.04)	0.75	0.03 (0.03)
0.00	0.75	0.08	0.05 (0.05)	0.99	0.04 (0.04)	0.00	0.03 (0.03)
0.25	0.75	0.08	0.05 (0.05)	0.99	0.04 (0.04)	0.25	0.03 (0.03)
0.50	0.75	0.08	0.05 (0.05)	1.00	0.04 (0.04)	0.50	0.03 (0.03)
0.75	0.75	0.08	0.04 (0.04)	1.00	0.04 (0.04)	0.75	0.03 (0.03)

6.4 Power Simulations

Power simulations were conducted to assess the probability of correctly rejecting $H_0 : \beta_G = 0$ at $\alpha = 0.05$. Figure 1 presents power curves at $n_0 = 10^3$ in the presence of unilateral missingness. Power curves under bilateral missingness are presented in supplementary Figure S3. The genetic effect on the target outcome β_G was varied between 0.037 and 0.14 to achieve heritabilities ranging from 0.1% to 1.0%, while the genetic effect on the surrogate outcome α_G was fixed at zero. In the absence of missingness, no additional power was gained by modeling the surrogate outcome. As the target missingness increased, the power of the

Table 2: **Empirical type I error of the Spray Wald test across $R = 5 \times 10^7$ simulation replicates in the presence of unilateral missingness**. The number of complete cases was $n_0 = 10^3$. The surrogate missingness was fixed at $\pi_S = 0$. The genetic effects were set to zero $\beta_G = \alpha_G = 0.00$, while the outcome variances were set to one, $\Sigma_{TT} = \Sigma_{SS} = 1.00$. The target missingness π_T and target-surrogate correlation ρ were varied. The point estimate is the average across simulation replicates.

Settings		**Type I Error**		
ρ	π_T	$\alpha = 0.05$ ($\times 10^2$)	$\alpha = 10^{-3}$ ($\times 10^3$)	$\alpha = 10^{-5}$ ($\times 10^5$)
0.00	0.00	5.10	1.08	1.09
0.25	0.00	5.10	1.08	1.21
0.50	0.00	5.09	1.07	1.09
0.75	0.00	5.08	1.07	1.20
0.00	0.25	5.10	1.07	1.17
0.25	0.25	5.10	1.08	1.20
0.50	0.25	5.09	1.06	1.06
0.75	0.25	5.08	1.05	1.07
0.00	0.50	5.11	1.07	1.14
0.25	0.50	5.11	1.07	1.18
0.50	0.50	5.10	1.08	1.14
0.75	0.50	5.08	1.06	1.16
0.00	0.75	5.12	1.09	1.22
0.25	0.75	5.12	1.07	1.22
0.50	0.75	5.11	1.07	1.12
0.75	0.75	5.09	1.06	1.06

SPRAY Wald test increased in correspondence with the target-surrogate correlation.

6.5 Empirical Relative Efficiency

Relative efficiency (RE) simulations were conducted comparing the SPRAY estimator $\hat{\beta}_G^{\text{Spray}}$ of β_G, which uses all available data, with the marginal estimator $\hat{\beta}_G^{\text{Marginal}}$ from the model:

$$T_i \big| (g_i, \boldsymbol{x}_i) \sim N\big(g_i \beta_G + \boldsymbol{x}_i' \boldsymbol{\beta}_X, \Sigma_{TT}\big),$$

which uses subjects with observed target outcomes only. These simulations quantify the efficiency gain attributable to incorporating information from the surrogate outcome. Ta-

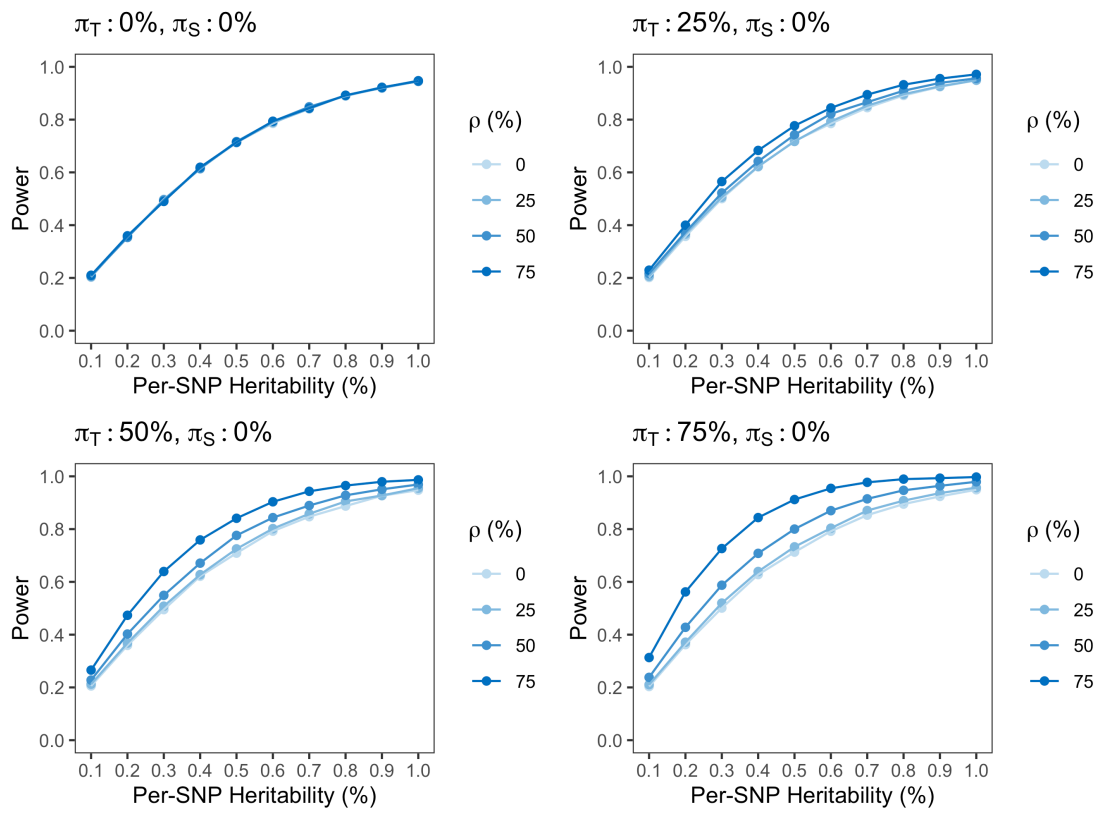

Figure 1: **Power curves for the Spray test of association in the presence of unilateral missingness**. The number of complete cases was $n_0 = 10^3$, and the type I error was $\alpha = 0.05$. Each point on the curve is the average across $R = 5 \times 10^5$ simulation replicates. The standard errors of the point estimates were negligible. The target regression coefficient β_G was varied between 0.037 and 0.14 to achieve heritabilities between 0.1% and 1.0%, while the surrogate regression coefficient α_G was fixed at zero. The surrogate missingness was held at $\pi_S = 0$, while the target missingness π_T and target-surrogate correlation ρ were varied.

ble 3 compares the empirical variances of $\hat{\beta}_G^{\text{Spray}}$ and $\hat{\beta}_G^{\text{Marginal}}$ in the presence of unilateral missingness, while supplemental Table S4 compares the empirical variances under bilateral missingness.

In the absence of target missingness ($\pi_T = 0$), or when the target-surrogate correlation was zero ($\rho = 0$), the empirical relative efficiency was 1.0, as predicted by (11). Thus, while jointly modeling the target and surrogate outcomes is unnecessary in the absence of missingness, power was not substantially diminished by modeling an uninformative surrogate. As the target missingness (π_T) and target-surrogate correlation (ρ) increased, the empirical RE increased as predicted by (11). The precise agreement between the empirical

and theoretical REs suggests that equation (11) could prove useful at the study design stage for assessing the expected efficiency gain provided by SPRAY.

Table 3: **Empirical relative efficiency of the Spray estimator to the marginal estimator of $\boldsymbol{\beta_G}$ test across $\boldsymbol{R = 5 \times 10^7}$ simulation replicates in the presence of unilateral missingness**. The number of complete cases was $n_0 = 10^3$. The true regression coefficients ($\beta_G = \alpha_G \approx 0.08$) were chosen such that the heritability of each outcome was 0.5%. The true variances of the target and surrogate outcomes were $\Sigma_{TT} = \Sigma_{SS} = 1.00$. The surrogate missingness was fixed at $\pi_S = 0.00$. The target missingness π_T and target-surrogate correlation ρ were varied. Variance refers to the empirical variance of the corresponding estimator across simulation replicates. The empirical RE is the ratio of the variance of $\hat{\beta}_G^{\text{Spray}}$ to that of $\hat{\beta}_G^{\text{Marginal}}$. The theoretical RE was obtained from (11).

Settings		**Variance**		**Relative Efficiency**	
ρ	π_T	Marginal	SPRAY	Empirical	Theoretical
0.00	0.00	0.0027	0.0027	1.0000	1.0000
0.25	0.00	0.0027	0.0027	1.0001	1.0000
0.50	0.00	0.0027	0.0027	1.0005	1.0000
0.75	0.00	0.0027	0.0027	1.0011	1.0000
0.00	0.25	0.0027	0.0027	0.9997	1.0000
0.25	0.25	0.0027	0.0026	1.0158	1.0159
0.50	0.25	0.0027	0.0025	1.0672	1.0667
0.75	0.25	0.0027	0.0023	1.1657	1.1636
0.00	0.50	0.0027	0.0027	0.9995	1.0000
0.25	0.50	0.0027	0.0026	1.0318	1.0323
0.50	0.50	0.0027	0.0023	1.1431	1.1429
0.75	0.50	0.0027	0.0019	1.3931	1.3913
0.00	0.75	0.0027	0.0027	0.9992	1.0000
0.25	0.75	0.0027	0.0026	1.0485	1.0492
0.50	0.75	0.0027	0.0022	1.2305	1.2308
0.75	0.75	0.0027	0.0016	1.7303	1.7297

7 Application to eQTL Mapping in GTEx

7.1 Material and Methods

7.1.1 Data Preparation

Genotypes and RNA transcript expression were obtained from the NHGRI Genotype Tissue Expression (GTEx) Project, Version 7 (phs000424.v7.p2). The sample consisted of subjects with expression in at least one of the substantia nigra (SSN) or whole blood. For inclusion, subjects were required to have genotypes, and complete data for age, sex, and genotyping platform. The overall sample size was $n = 395$. Among these, there were $n_0 = 47$ (12%) complete cases, $n_1 = 322$ (82%) subjects with target missingness, and $n_2 = 26$ (7%) subjects with surrogate missingness. Loci were excluded from the analysis if the per-locus missingness exceeded 10% or if the minor allele frequency fell below 5%. The top 3 PCs of the empirical GRM were calculated in `PLINK` (Purcell et al., 2007). To reduce multiple testing, variants in LD ($R^2 > 0.8$) were greedily pruned within a 1 Mb sliding window. A transcript was considered *expressed* if the raw read count exceeded 5 for at least 20% of subjects in both SSN and blood. For sequences with multiple isoforms, only the isoform with the greatest variation in expression across subjects was retained. Expression levels were normalized within tissues via the rank-based inverse normal transformation (INT) (McCaw et al., 2019), ensuring that the marginal distributions of the target and surrogate outcomes were each normal.

7.1.2 Association Testing

Association tests were performed for all variants in *cis* to the transcript's expressed sequence, defined as residing in the region spanning from 1 Mb upstream of the transcription start site to 1 Mb downstream of the transcription end site. Across the 17,007 expressed transcripts, the number of loci in *cis* ranged from 24 to 4,834, with a median of 887. A separate test of association was conducted for each *cis*-locus by expressed transcript pairing.

For the marginal analysis, transcript expression in SSN T_i was regressed on genotype,

covariates, and genetic PCs, according to the association model:

$$T_i = \beta_0 + \beta_G g_i + \beta_A \text{Age}_i + \beta_S \text{Sex}_i + \beta_P \text{Platform}_i + \boldsymbol{\beta}'_{PC} \text{PCs}_i + \epsilon_{T,i}, \tag{12}$$

where $\epsilon_{T,i}$ is a residual with mean zero and finite variance. The target of inference was β_G. The null hypothesis $H_0 : \beta_G = 0$ was assessed using the standard Wald test, with p-values estimated from the χ^2_1 distribution. Only the $n_0 + n_2 = 73$ subjects with observed expression in SSN were included in the marginal analysis. Note that expression in blood S_i was excluded from the marginal analysis, since conditioning on S_i in the regression model would change the interpretation of β_G (see Section 5.1).

For the joint analysis, expression in SSN T_i and in blood S_i were jointly regressed on genotype, covariates, and genetic PCs, according to the Spray model:

$$\begin{pmatrix} T_i \\ S_i \end{pmatrix} = \begin{pmatrix} \beta_0 + \beta_G g_i + \beta_A \text{Age}_i + \beta_S \text{Sex}_i + \beta_P \text{Platform}_i + \boldsymbol{\beta}'_{PC} \text{PCs}_i \\ \alpha_0 + \alpha_G g_i + \alpha_A \text{Age}_i + \alpha_S \text{Sex}_i + \alpha_P \text{Platform}_i + \boldsymbol{\alpha}'_{PC} \text{PCs}_i \end{pmatrix} + \begin{pmatrix} \epsilon_{T,i} \\ \epsilon_{S,i} \end{pmatrix},$$

where $(\epsilon_{T,i}, \epsilon_{S,i}) = \boldsymbol{\epsilon}_i \overset{\text{IID}}{\sim} N(\mathbf{0}, \boldsymbol{\Sigma})$. Estimation and inference were performed using the accompanying `R` package (`SurrogateRegression`). ECME iterations continued until the improvement in the observed data log likelihood dropped below 10^{-8}. The null hypothesis $H_0 : \beta_G = 0$ was evaluated using the Spray Wald test. All $n = 395$ subjects with expression in at least one of SSN or blood were included in the joint analysis.

7.2 Results

7.2.1 Discovery and Efficiency Gains

In total, $16,108,176$ tests of association were performed. Each test compared expression of a single transcript with genotype at a single locus in *cis*. Genome-wide significance was declared at $\alpha = 5 \times 10^{-8}$ (Pe'er et al., 2008). Marginal association analysis, using observed expression in the SSN only, identified 294 significant associations, occurring between 90

unique transcripts and 272 unique genetic variants. Joint association analysis via SPRAY, using expression in both SSN and blood, identified 820 significant associations, occurring between 223 unique transcripts and 745 unique genetic variants.

Figure 2 compares the estimated effect sizes, p-values, and empirical relative efficiency of SPRAY and the marginal association analysis at SNPs that achieved genome-wide significance in either analysis. All SNPs that reached significance in the marginal analysis were also significant according to SPRAY, but not conversely. Panel A demonstrates that the estimated effect sizes were highly concordant ($R^2 = 0.998$), while panel B demonstrates that the SPRAY test of association was as or more significant than the marginal test. These observations verify that that the estimand of SPRAY coincides with that from marginal association analysis, and suggest that the power gain realized by SPRAY was achieved primarily through increasing the precision. Indeed, panel C demonstrates that the empirical relative efficiency, as the ratio of $\mathrm{Var}(\hat{\beta}_G^{\mathrm{Marginal}})$ to $\mathrm{Var}(\hat{\beta}_G^{\mathrm{Spray}})$, always exceeded 1, and as predicted by (11), increased with the square correlation (r^2) between expression in SSN and expression in whole blood.

Table 4 presents the discovery and average efficiency gains of SPRAY over the marginal association analysis. The *discovery gain* was defined as the number of significant eQTL uniquely detected by SPRAY relative to the number of significant eQTL detected by either analysis. Among the 820 eQTL identified by either analysis, all 820 were detected by SPRAY, and 526 were detected by SPRAY alone. The discovery gain was thereby 64.1% (= 526/820). The *average efficiency gain* was defined as the ratio of the average sampling variance of the marginal estimated $\overline{\mathrm{Var}}(\hat{\beta}_G^{\mathrm{Marginal}})$, across the 820 significant eQTL, to the average sampling variance of the SPRAY estimator, $\overline{\mathrm{Var}}(\hat{\beta}_G^{\mathrm{Marginal}})$, minus 1. The average efficiency gain was 19.6% ($= 0.024/0.020 - 1$).

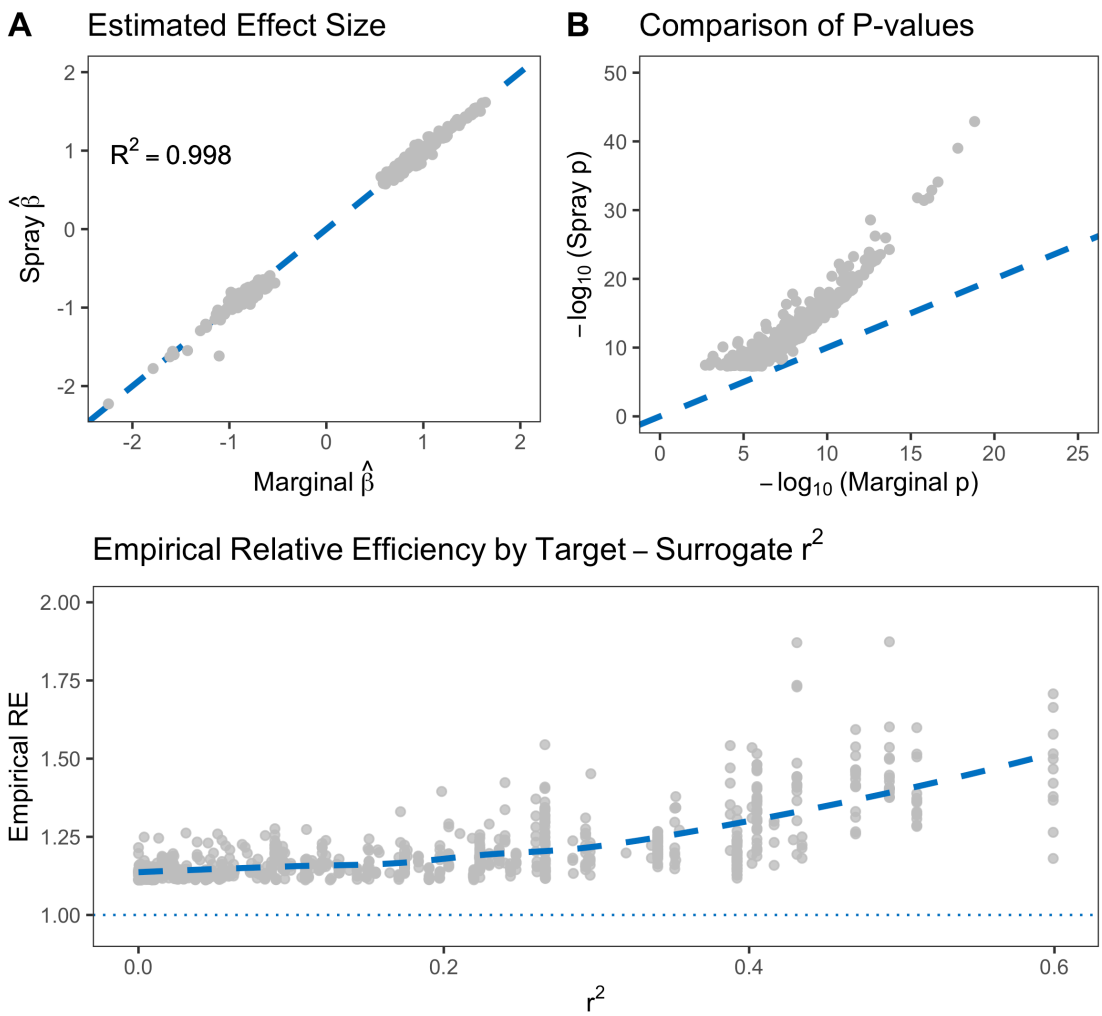

Figure 2: **Comparison of effect sizes, p-values, and empirical relative efficiency between Spray and the marginal association analyses at genome-wide significant *cis*-eQTL in SSN.** The marginal association test uses observed expression in SSN only, while the joint association test (Spray) uses expression in SSN and in blood. Panel A compares the effect sizes estimated by Spray and by the marginal analysis, while panel B compares the p-values. Panel C plots the empirical relative efficiency, the ratio of $\mathrm{Var}(\hat{\beta}_G^{\mathrm{Marginal}})$ to $\mathrm{Var}(\hat{\beta}_G^{\mathrm{Spray}})$, as a function of the square correlation between expression in SSN and expression in blood.

7.2.2 Functional Analysis

The biological role of the candidate eQTL identified by Spray was evaluated using FUMA (Watanabe et al., 2017). At the recommended LD threshold of $R^2 \geq 0.6$, the 745 unique genetic variants identified by Spray resolved to 361 independent significant associations,

Table 4: **Discovery and average efficiency gains of Spray relative to the marginal association analysis**. Significant associations were declared at ($\alpha = 5 \times 10^{-8}$). The discovery gain is the number of associations uniquely identified by Spray relative to the number of associations identified by either analysis. The efficiency gain is one less than the empirical relative efficiency of the Spray estimator to the marginal estimate of the genetic effect of averaged over the 820 significant eQTL identified by Spray.

Significant Associations		
Spray	Marginal	Discovery Gain (%)
820	294	64.1
Average Estimator Variance		
Spray	Marginal	Efficiency Gain (%)
0.020	0.024	19.6

belonging to 183 distinct genomic loci. Meanwhile, the 272 unique genetic variants identified by the marginal analysis collapsed to only 122 independent significant associations, belonging to 77 distinct genomic loci. All 77 genomic loci associated with gene expression in SSN by the marginal analysis were also identified by Spray. The 106 ($= 183 - 77$) loci identified by Spray only, each harbored at least 1 previously reported GWAS variant (MacArthur et al., 2017). An interesting example is a locus on chromosome 1, spanning base pairs 74,476,321 to 74,710,629. The lead SNP (1_74710629_C_T_b37; alias rs483259) was significantly associated with decreased expression of the protein-coding LRRIQ3 gene ($\hat{\beta}_G = -0.85$; 95% CI -1.12 to -0.59; $p = 2 \times 10^{-10}$) via Spray. This SNP is in LD with two nearby SNPs, rs10789387 ($R^2 = 0.66$) and rs11210400 ($R^2 = 0.66$), both of which were recently associated with increased educational attainment, at $p = 7 \times 10^{-16}$ and $p = 2 \times 10^{-17}$, in a meta-analysis of $n > 1.1 \times 10^6$ subjects (Lee et al., 2018). Further work is needed to investigate whether the association of the meta-analysis SNPs with educational attainment is partially mediated by decreased expression of the LRRIQ3 gene.

8 Discussion

We have proposed Surrogate Phenotype Regression Analysis (Spray) as a novel approach to eQTL mapping in the presence of missing data, and derived a computationally efficient, ECME-type algorithm for fitting the underlying association model. We have demonstrated analytically and empirically, though extensive simulations and in real data, that the Spray test of association, which incorporates information from the target and surrogate outcomes, is more powerful than the marginal test of association, which incorporates information from the target outcome only.

We derived and validated a simple formula for assessing the efficiency gain achieved by Spray over marginal association analysis. This efficiency gain increases with the target missingness, and with the square of the target-surrogate correlation. We applied Spray to eQTL mapping in GTEx, using expression in SSN as the target outcome and expression in blood as the surrogate outcome. Spray identified 64.1% more significant *cis*-eQTL than marginal eQTL mapping. Although the joint and marginal effect size estimates were highly concordant ($R^2 = 0.998$), the association statistics estimated by Spray had 19.6% greater precision on average. All estimation and inference procedures described in this article have been implemented in the accompanying `R` package (McCaw, 2020).

The problem of cross-tissue eQTL mapping has not previously been studied from the missing data perspective. Established software for eQTL mapping, such as `MatrixEQTL` (Shabalin, 2012), either address missing data via complete case analysis, which is inefficient, or via mean imputation, which invalidates inference. Although sophisticated methods exist for imputing gene expression across tissues (Wang et al., 2016), inference after single imputation leads to inflated type I error (Little and Rubin, 2002), and multiple imputation is computationally infeasible when performing in excess of 16×10^6 association tests at $\alpha = 5 \times 10^{-8}$. Spray fills this gap by providing a valid, powerful, and computationally tractable approach to eQTL mapping in the presence of missing data.

Our work suggests several areas for further improvement. Although the inverse normal transformation may be applied to ensure the marginal distributions of the target and surrogate outcomes are normal, bivariate normality of the two outcomes is not guaranteed. A future direction is to develop association tests that allow for arbitrary patterns of outcome missingness but do not require specification of joint distribution of the target and surrogate outcomes. Instead of maximum likelihood based estimation, this procedure could use a set of inverse probability weighted estimating equations (Robins et al., 1995). Another avenue for future development is to incorporate multiple surrogate outcomes. One way to achieve this would be to extend the bivariate normal regression framework to a multivariate normal regression framework. However, there are drawbacks to directly modeling multiple surrogate outcomes: the number of nuisance covariance parameters increases quadratically with the number of surrogates, while the number of potential missingness patterns increases exponentially. Finally, although the current work was motivated by eQTL mapping, the idea of leveraging a surrogate outcome to improve inference on a partially missing target outcome is broadly applicable. For example, in large cohort studies such as the UK Biobank (Allen et al., 2014), the target outcome may be an incompletely ascertained phenotype, such as the concentration of a biomarker only measured for a subset of participants, while the surrogate outcome may be a readily ascertained phenotype, such as diagnostic codes from electronic health records.

Software

The standard univariate test was implemented using base `R`. `SPRAY` is available at `https://CRAN.R-project.org/package=SurrogateRegression`. Links to this and related software may also be found at `https://content.sph.harvard.edu/xlin/software.html`.

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