

Batch Effects

Solutions to avoid batch effects and remove bias

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Batch effects

The problem: Batch effects and other technical artifacts can seriously bias and obscure signal in high-throughput experiments.

Potential solutions:

Record information:

Report date, reagent changes, personnel changes, etc.

Good experimental design:

Balance with respect to batches, etc.

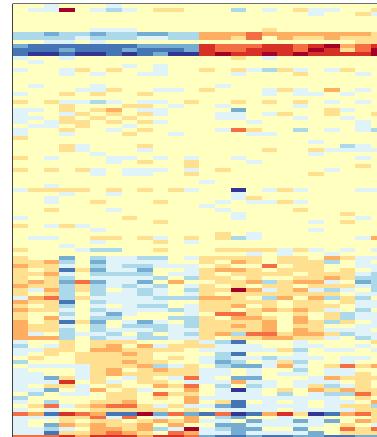
Statistical correction:

Simple regression when variables are known, and surrogate variable analysis (for example) when they unknown or uncertain.

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12 males and females, 2 months, 109 genes

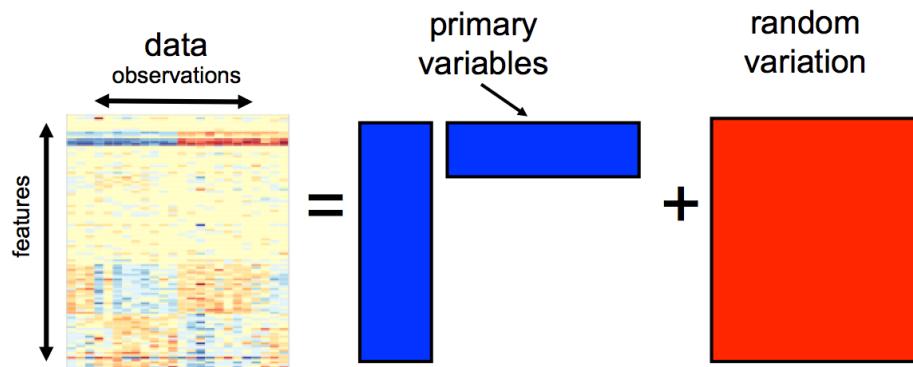
	Female	Male
June 2005	3	9
October 2005	9	3



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[RI]

Decomposing variability

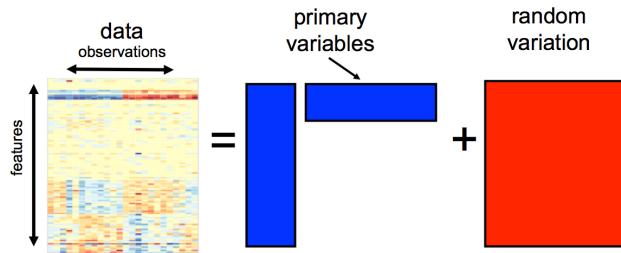


$$Y_{m,n} = \beta_{m,p} X_{p,n} + \varepsilon_{m,n}$$

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[RI]

We model sex using this parametrization



$$Y_{m,n} = \beta_{m,p} X_{p,n} + \varepsilon_{m,n}$$

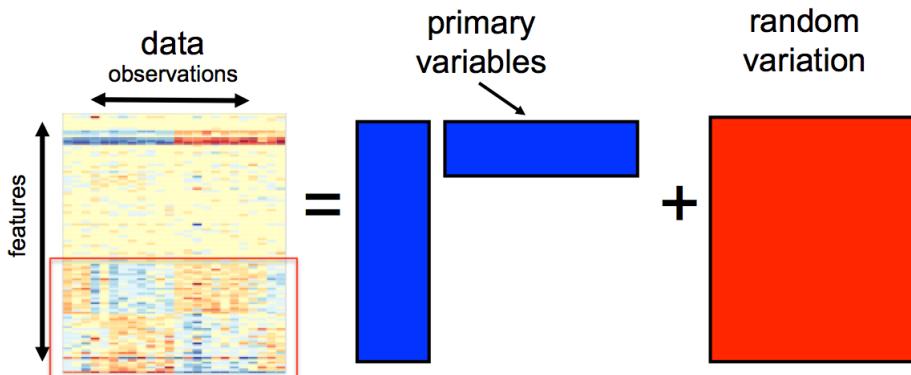
$$\beta_{m \times p} = \begin{pmatrix} \beta_{1,0} & \beta_{1,1} \\ \vdots & \\ \beta_{m,0} & \beta_{m,1} \end{pmatrix}$$

$$X_{p \times n} = \begin{pmatrix} 1 & 0 \\ 1 & 0 \\ \vdots & \\ 1 & 0 \\ 1 & 1 \\ 1 & 1 \\ \vdots & \\ 1 & 1 \end{pmatrix}^T$$

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This model does not account for batch

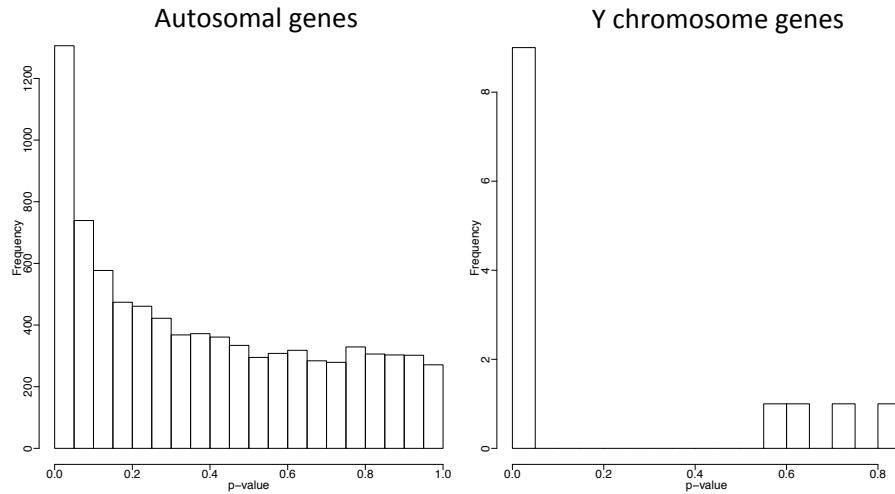


$$Y_{m,n} = \beta_{m,p} X_{p,n} + \varepsilon_{m,n}$$

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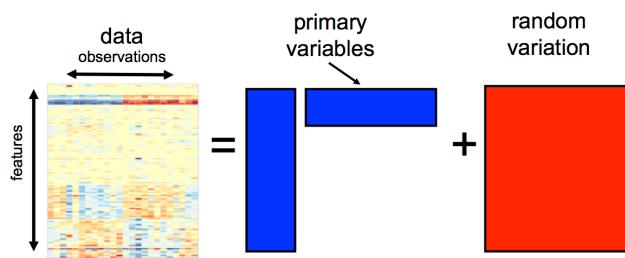
P-values



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We can include a term for batch



$$Y_{m,n} = \beta_{m,p} X_{p,n} + \varepsilon_{m,n}$$

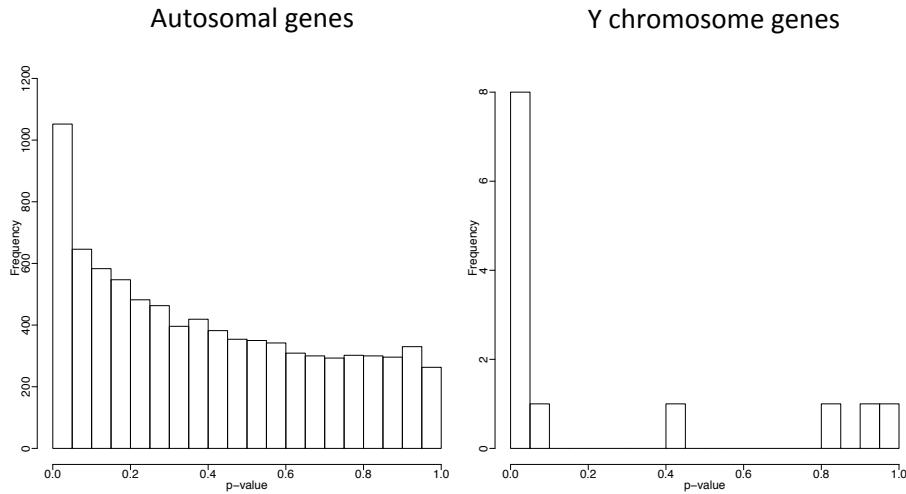
$$\beta_{m \times p} = \begin{pmatrix} \beta_{1,0} & \beta_{1,1} & \beta_{1,2} \\ \vdots & & \\ \beta_{m,0} & \beta_{m,1} & \beta_{m,2} \end{pmatrix}$$

$$X_{p \times n} = \begin{pmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 1 \\ \vdots & & \\ 1 & 0 & 1 \\ 1 & 1 & 0 \\ \vdots & & \\ 1 & 1 & 0 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix}^T$$

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[RI]

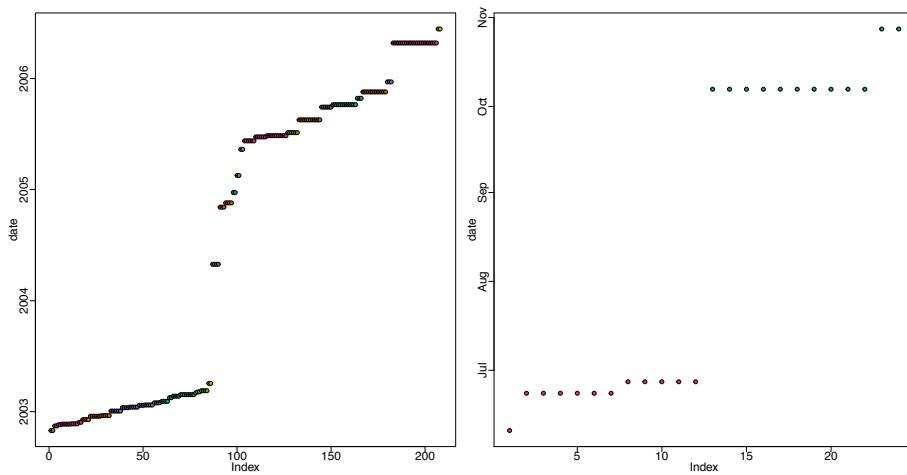
P-values after adjusting for batch



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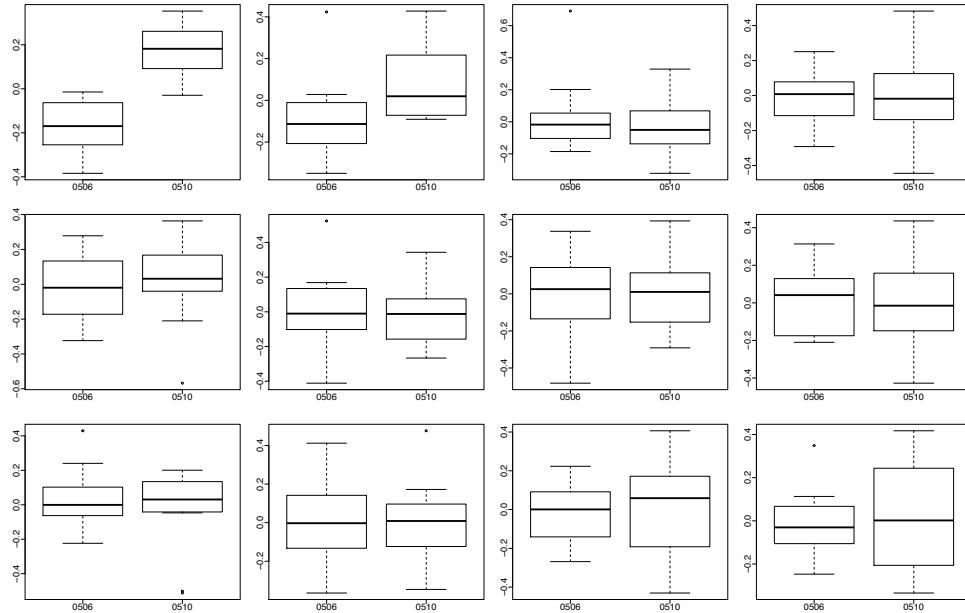
Do we know what the batches are?



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[RI]

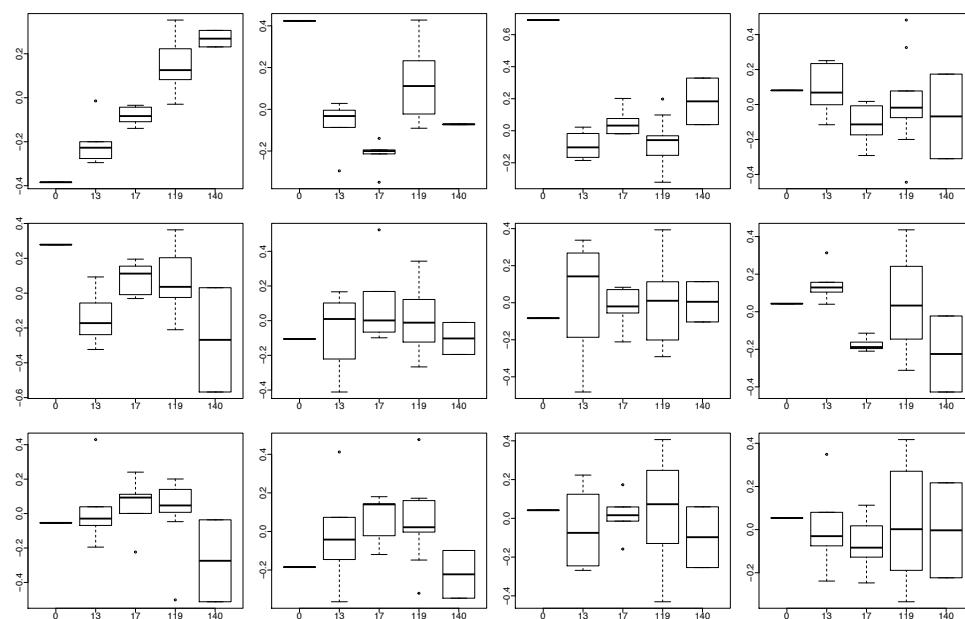
How many eigenvectors explain batch?



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[RI]

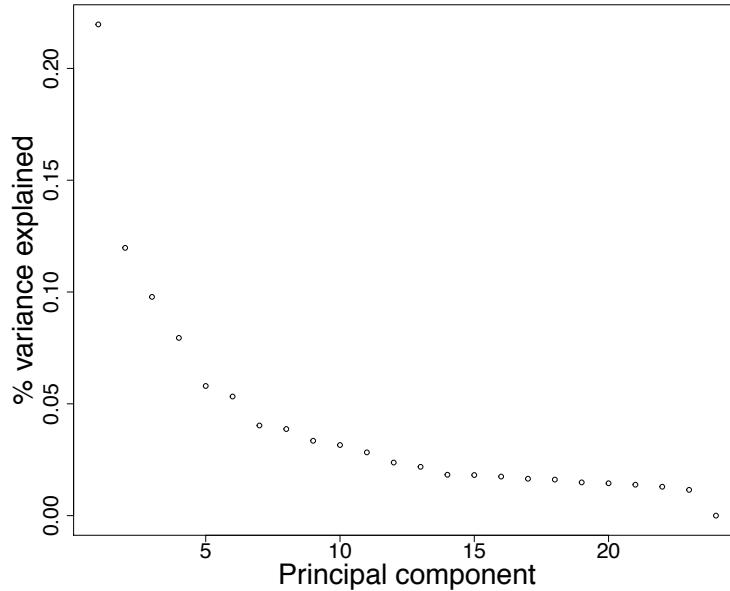
How many eigenvectors explain batch?



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Variability explained



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Batch surrogates

The first k columns give us estimates of surrogates

$$Y_{m \times n} = U_{m \times k} D_{k \times k} V'_{k \times n} + \varepsilon_{m \times n}$$

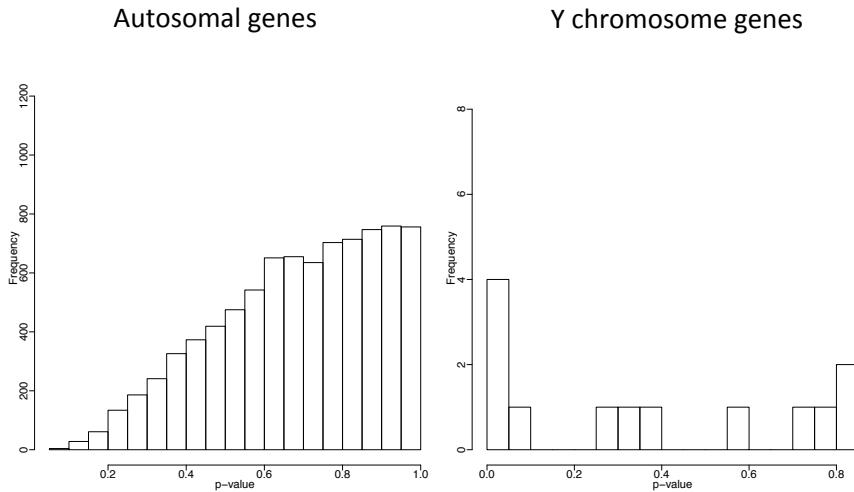
which can also be written like this:

$$Y_{m \times n} = \gamma_1 V'_1 + \cdots + \gamma_k V'_k + \varepsilon_{m \times n}$$

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P-values after regressing out 6 PCs

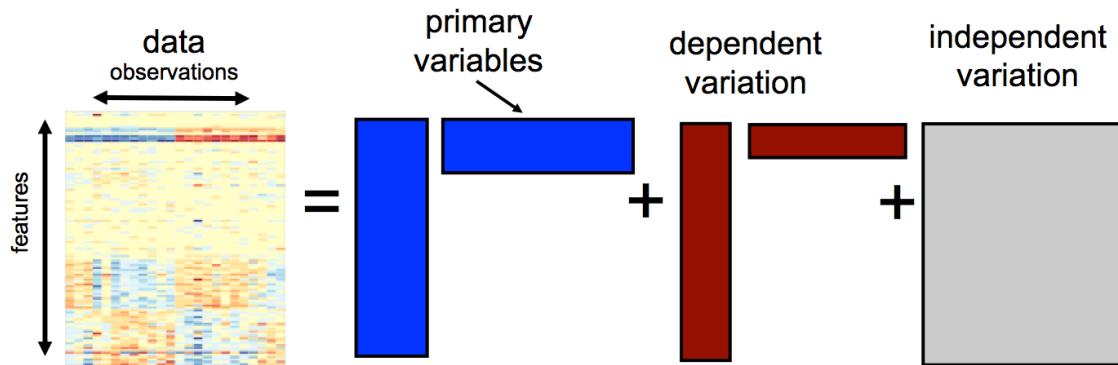


We washed away the signal!

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SVA fits this model

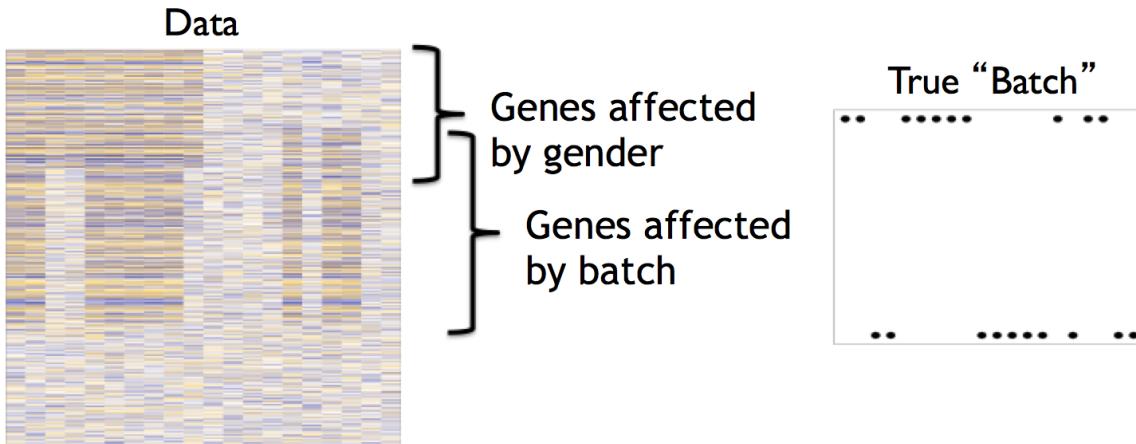


$$Y_{m \times n} = \beta_{m \times p} X_{p \times n} + \alpha_{m \times k} W_{k \times n} + \varepsilon_{m \times n}$$

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[RI]

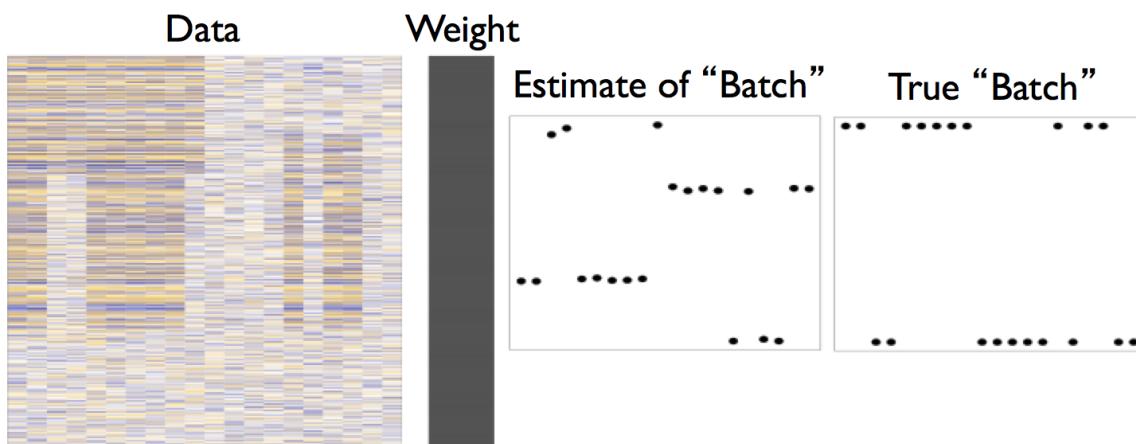
Surrogate variable analysis



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[JL]

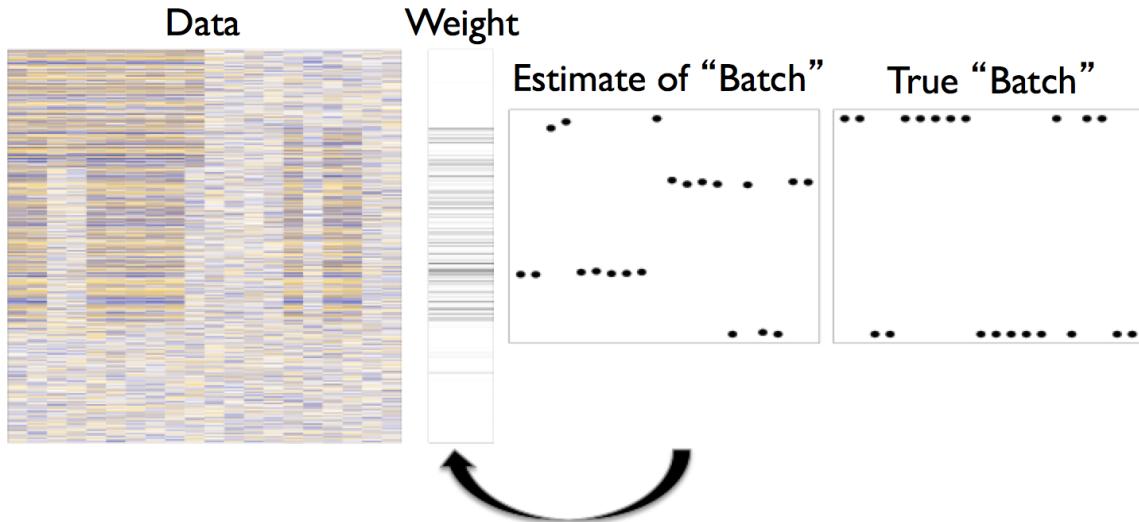
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[JL]

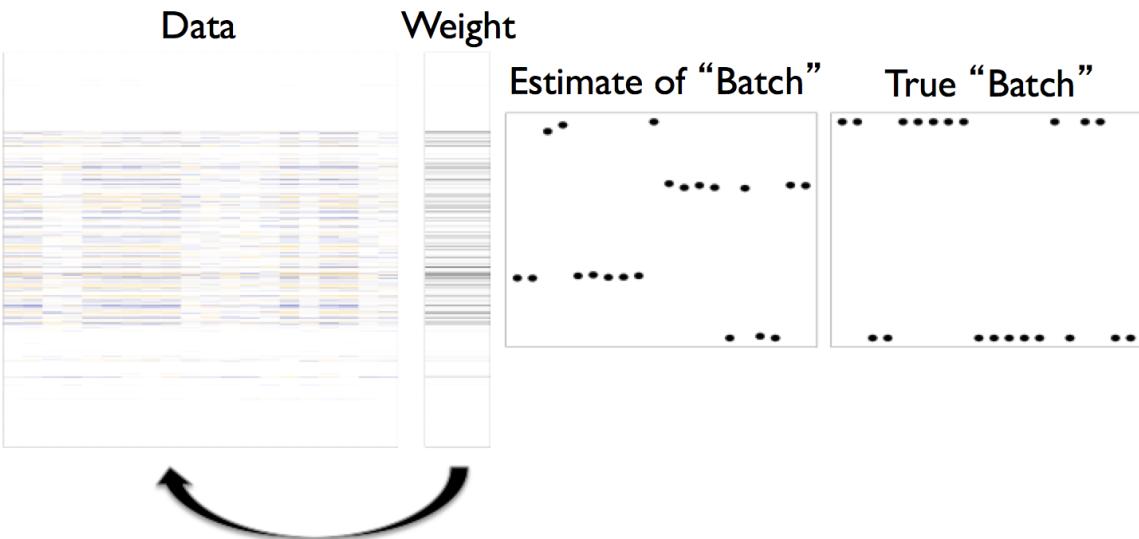
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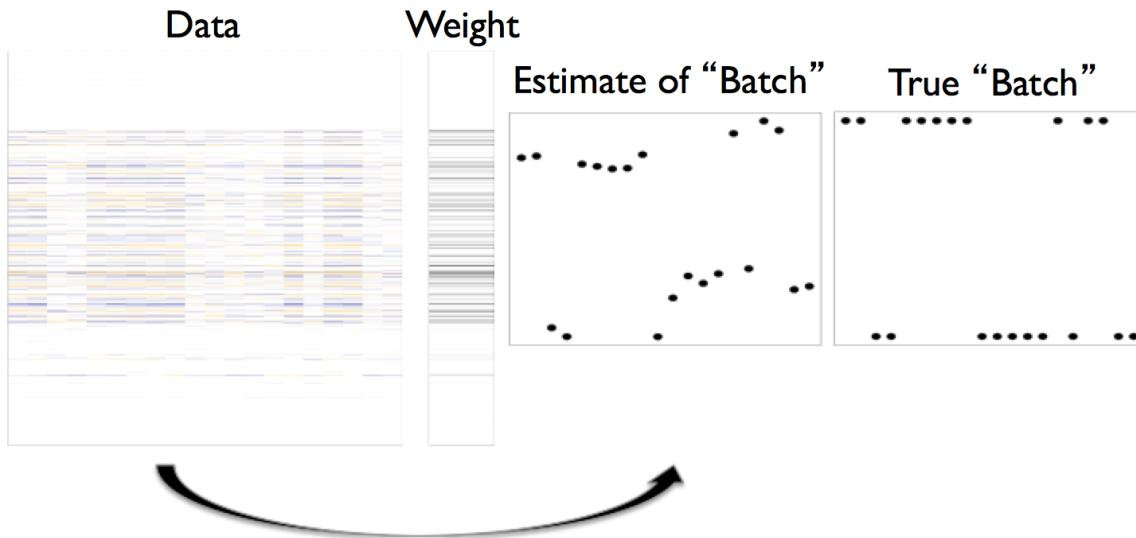
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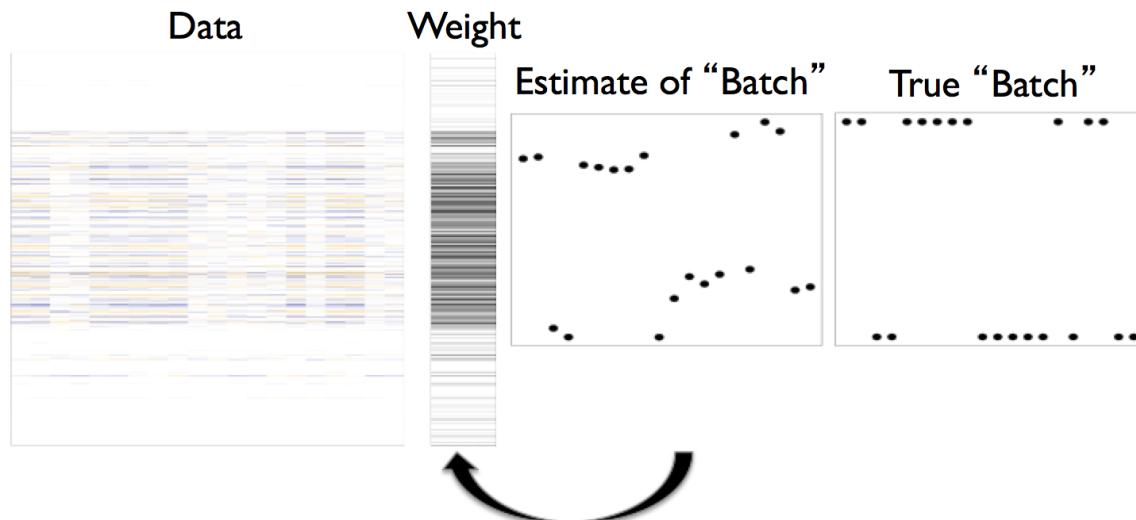
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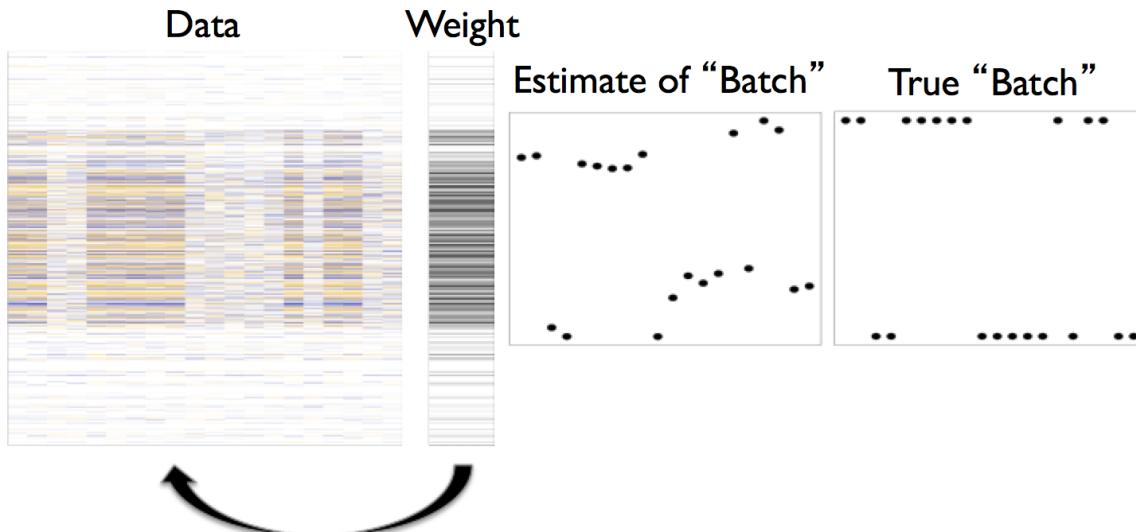
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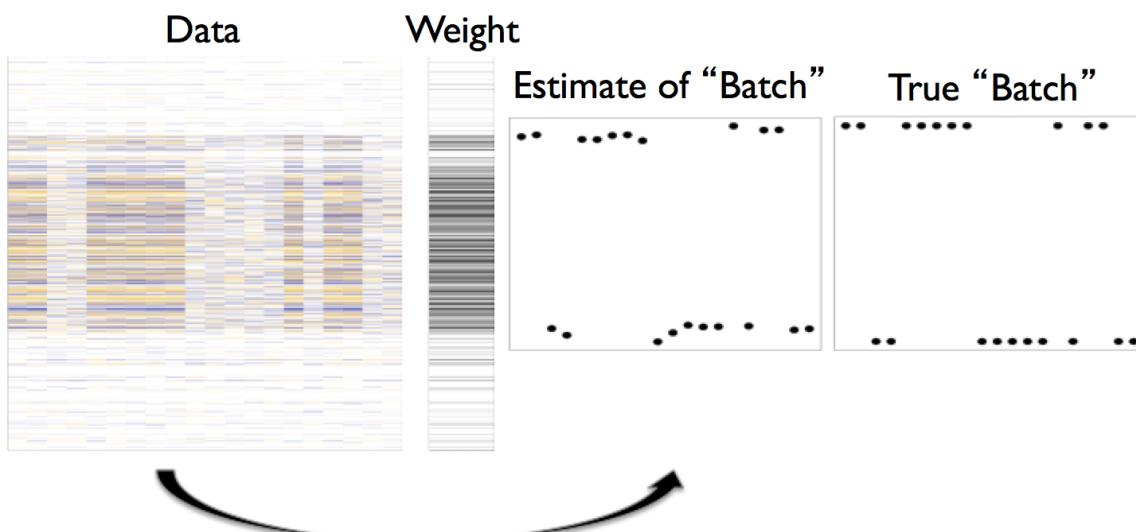
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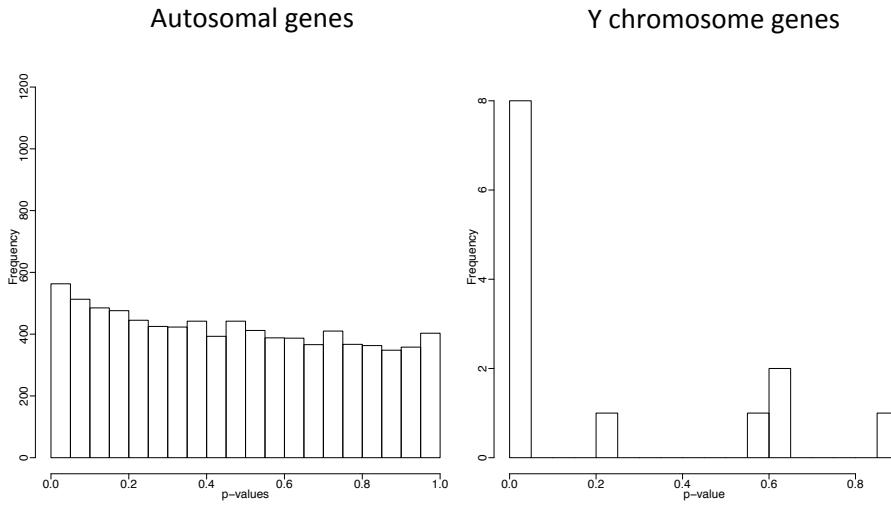
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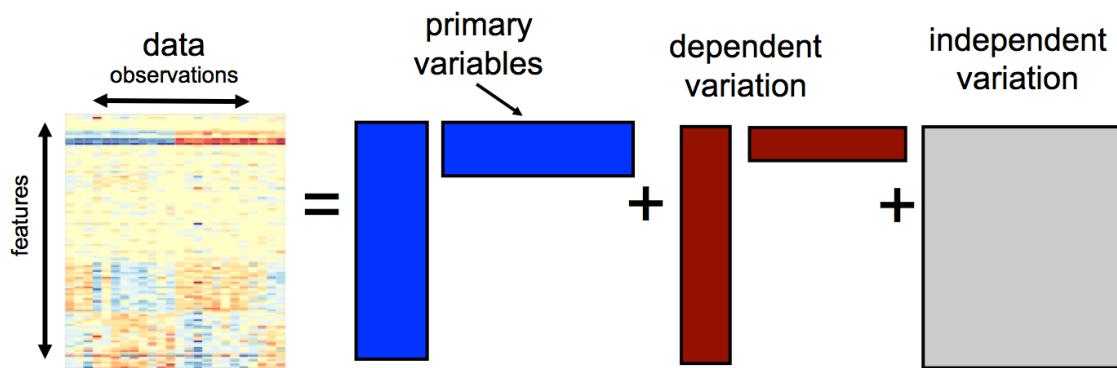
P-values after SVA



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[RI]

SVA fits this model

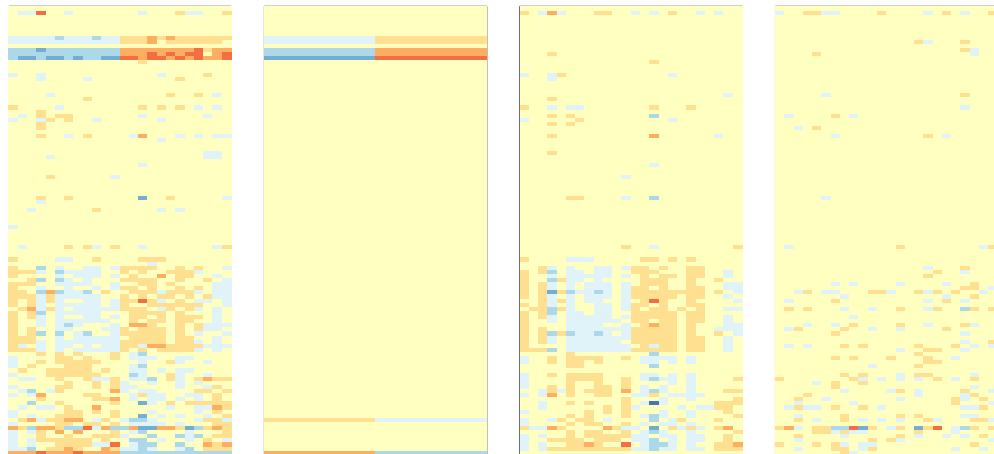


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Decomposed data



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