# The heterosis problem: a comparison of Eric's method with edgeR, baySeq, and ShrinkBayes

Will Landau, Eric Mittman

Iowa State University

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imulated data

The contenders
edgeR
ShrinkBayes

# The problem

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# Mock heterosis data

		Parent (1)				Pare	arent (2)			Hybrid (3)			Truth	
HPH	Feature 1	3	4	2	1	0	0	1	0	700	900	825	860	1
HPH	Feature 2	0	1	1	0	2	7	5	18	50	501	400	90	1
	Feature 3	100	225	0	15	300	106	200	400	70	279	100	123	0
LPH	Feature 4	893	400	760	901	1000	513	760	580	5	5	6	7	1
	Feature 25000	10	13	6	4	902	912	999	825	819	761	800	465	0

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# Simulation workflow

- Simulate 30 datasets:
  - 10 datasets with 4 samples (libraries, columns, etc.) per group
  - ▶ 10 with 8 per group
  - ▶ 10 with 16 per group
- For each simulated dataset, test for heterosis with
  - empirical Bayes with STAN (Eric's method)
  - edgeR
  - baySeq
  - ▶ ShrinkBayes
- Compare methods with ROC curves

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# Simulated data

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Simulated data

# Apply edgeR to real data to get simulation parameters

Normalization factors



Main effects and dispersions

Parent (1)	Parent (2)	Hybrid (3)	Dispersion
$\mu_{1,1}$	$\mu_{1,2}$	$\mu_{1,3}$	$\psi_1$
$\mu_{2,1}$	$\mu_{2,2}$	$\mu_{2,3}$	$\psi_2$
$\mu_{27888,1}$	$\mu_{27888,2}$	$\mu_{27888,3}$	$\psi_{27888}$

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# Generating the data

▶ Does feature *f* truly have heterosis?

truth<sub>f</sub> = 
$$I(\mu_{f,3} > \max(\mu_{f,1}, \mu_{f,2}))$$
 or  $\mu_{f,3} < \min(\mu_{f,1}, \mu_{f,2})$ 

For a dataset with 4 libraries per group,

$$y_{f,i} \stackrel{\text{iid}}{\sim} NB \left( \exp \left( c_i + \mu_{f,t(i)} \right), \ \psi_f \right)$$

- $\blacktriangleright$  t(i) is the group of library i.
- ▶ Resimulate to increase the number of libraries per group.
- Remove extremely low-count features.
- ► Take a random subset of 25000 features from the remaining ones.

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# Mock example data with 4 samples per treatment group

			Parent (1)		Parent (2)			Hybrid (3)				Truth			
HPH (	Feature 1	3	4	2	1	0	0	1	0	700	900	825	860		1
HPH (	Feature 2	0	1	1	0	2	7	5	18	50	501	400	90		1
	Feature 3	100	225	0	15	300	106	200	400	70	279	100	123		0
LPH (	Feature 4	893	400	760	901	1000	513	760	580	5	5	6	7		1
														_	
	Feature 25000	10	13	6	4	902	912	999	825	819	761	800	465	-	0

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edgeR ShrinkBaye: bavSeq

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ROC (receiver operating characteristic) curves

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edgeR ShrinkBayes

- ▶ Fit a loglinear model to estimate main effects  $\mu_{f,t}$ 
  - Feature f = 1, ..., 25000
  - ▶ Treatment group t = 1 (parent), 2 (parent), 3 (hybrid)
- ▶ Likelihood ratio tests to get p-values  $p_{f,1}$ ,  $p_{f,2}$

$$H_{0,1}: \mu_{f,3} = \mu_{f,1}$$
  $H_{a,1}: \mu_{f,3} \neq \mu_{f,1}$   
 $H_{0,2}: \mu_{f,3} = \mu_{f,2}$   $H_{a,2}: \mu_{f,3} \neq \mu_{f,2}$ 

Final p-value:

$$p_{f, \text{edgeR}} = \begin{cases} p_{f,1}/2 & \widehat{\mu}_{f,3} < \widehat{\mu}_{f,1} \leq \widehat{\mu}_{f,2} \text{ or } \widehat{\mu}_{f,3} > \widehat{\mu}_{f,1} \geq \widehat{\mu}_{f,2} \\ p_{f,2}/2 & \widehat{\mu}_{f,3} < \widehat{\mu}_{f,2} \leq \widehat{\mu}_{f,1} \text{ or } \widehat{\mu}_{f,3} > \widehat{\mu}_{f,2} \geq \widehat{\mu}_{f,1} \\ 1 & \widehat{\mu}_{f,1} \leq \widehat{\mu}_{f,3} \leq \widehat{\mu}_{f,2} \text{ or } \widehat{\mu}_{f,2} \leq \widehat{\mu}_{f,3} \leq \widehat{\mu}_{f,1} \end{cases}$$

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- Built on inla (integrated nested Laplace approximation).
- empirical Bayes with a zero-inflated NB likelihood and normal priors.
- ▶ I reparameterize

$$\begin{split} \phi_f &= \frac{\mu_{f,1} + \mu_{f,2}}{2} \qquad \text{(parental mean)} \\ \alpha_f &= \frac{\mu_{f,2} - \mu_{f,1}}{2} \qquad \text{(half parental difference)} \\ \delta_f &= \mu_{f,3} - \frac{\mu_{f,1} + \mu_{f,2}}{2} \qquad \text{(hybrid effect)} \end{split}$$

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ShrinkBayes

 $\alpha_f = \text{ half parental difference}$   $\delta_f = \text{ hybrid effect}$ 

Use contrasts to calculate final posterior probabilities of heterosis:

$$p_{f,\mathtt{ShrinkBayes}} = \begin{cases} 0 & \left| \widehat{\delta}_f \right| < \left| \widehat{\alpha}_f \right|, \, \mathsf{o.w.:} \\ P(\delta_f + \alpha_f > 0 \mid \mathsf{data}) & \widehat{\delta}_f > -\widehat{\alpha}_f \\ P(\delta_f - \alpha_f > 0 \mid \mathsf{data}) & \widehat{\delta}_f > \widehat{\alpha}_f \\ P(\delta_f - \alpha_f < 0 \mid \mathsf{data}) & \widehat{\delta}_f < \widehat{\alpha}_f \\ P(\delta_f + \alpha_f < 0 \mid \mathsf{data}) & \widehat{\delta}_f < -\widehat{\alpha}_f \end{cases}$$

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ROC (receiver operating characteristic) curves

The results

- ▶ Estimate main effects  $\mu_{f,t}$  using edgeR.
- Calculate the posterior probability that each feature satisfies:

Model	Constraint
$M_1$	All $\mu_{f,t}$ 's equal
$M_2$	$\mu_{f,1} = \mu_{f,2}$
$M_3$	$\mu_{f,1} = \mu_{f,3}$
$M_4$	$\mu_{f,2} = \mu_{f,3}$
$M_5$	All $\mu_{f,t}$ 's distinct

► Final posterior probabilities of heterosis:

$$p_{f, \text{baySeq}} = \begin{cases} 0 & \widehat{\mu}_{f, 1} \leq \widehat{\mu}_{f, 3} \leq \widehat{\mu}_{f, 2} \text{ or} \\ \widehat{\mu}_{f, 2} \leq \widehat{\mu}_{f, 3} \leq \widehat{\mu}_{f, 1} \end{cases}$$

$$P(M_2 \mid \text{data}) + P(M_5 \mid \text{data}) \quad \text{otherwise}$$

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ROC (receiver operating characteristic) curves

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ROC (receiver operating characteristic) curve: The results

- $\triangleright$   $N_{\text{true}}$  heterosis features,  $N_{\text{false}}$  null features.
- ► Results of testing each feature for heterosis (25000 columns here):

rank	0.802	0.935	0.539	0.001		0.500	0.603
truth	0	0	1	1		1	0

Sort table by p-value (or other binary classifier)

rank	0.000	0.001	0.005	0.006		0.901	1.000
truth	1	1	0	1		0	0

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edgeR ShrinkBayes baySeq

ROC (receiver operating characteristic) curves The results ▶ In practice, we would declare the lowest-p-value features to have heterosis.

rank	0.000	0.001	0.005	0.006		0.901	1.000
truth	1	1	0	1	• • •	0	0

▶ With 2 heterosis genes and 1 null gene,

$$FPR = \frac{1}{N_{false}}$$
  $TPR = \frac{2}{N_{true}}$ 

Repeat for multiple cutoffs to get multiple (FPR, TPR) pairs.

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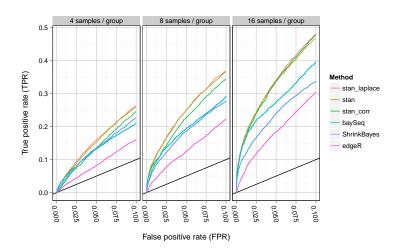
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# Example ROC curves



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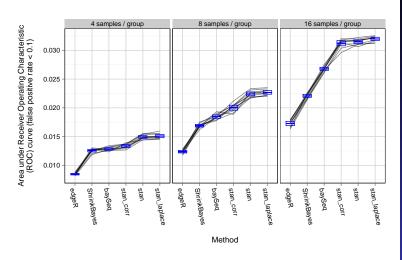
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baySeq

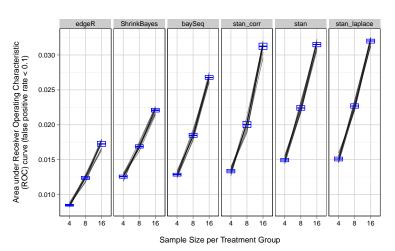
# Areas under ROC curves



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# Areas under ROC curves



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ROC (receiver operating characteristic) curves

The results