

From sequence ...

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Genomic Feature Model Analysis of Complex Traits

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Data

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- **Whole-genome sequences** and **multiple novel trait phenotypes**
from large numbers of individuals from **multiple populations**

Enable us to **better understand genetic architecture** of complex traits

- **disentangle genetic variation**
- **disentangle genetic correlation**

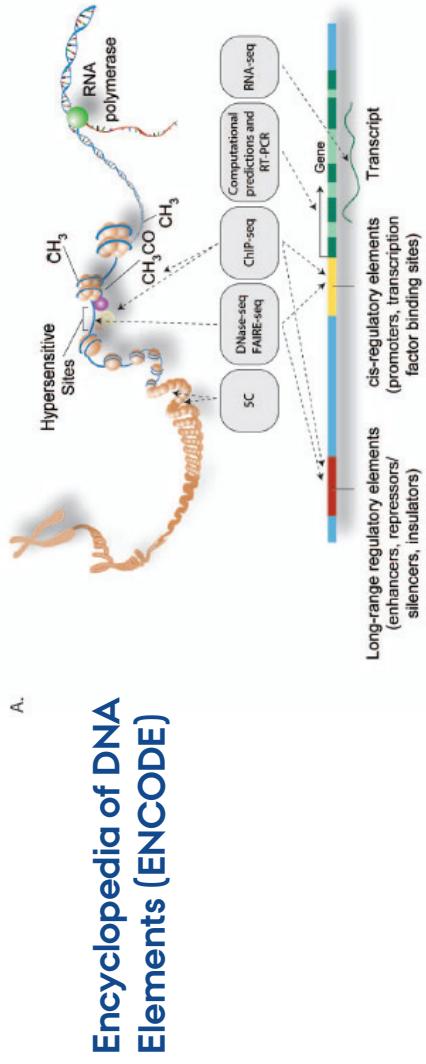
Two important parameters for **prediction of trait phenotypes**
and **consequences of selection decisions** in breeding programs

More data

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A.



• **Molecular phenotypes** (transcriptome, proteome or metabolome) associated to the traits/diseases of interest

• **Molecular-interaction maps** that provide insight into the structural and functional organization of their genomes

What to do?

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- How do we translate the massive collection of data at different levels of biology into useful biological knowledge?
- Can we use these different layers of data to improve predictive models of complex traits and diseases?
- Which statistical modeling approaches should we use?

Genomic feature models

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- **Statistical modeling approach** that evaluates the collective action of sets of genetic variants defined by a genomic feature: “**...model a feature of the genome**”
- **Genomic features are defined by grouping** genetic variants according to a certain classification scheme such as:
 - Chromosomes/Genes
 - Biological Pathways
 - Gene or Sequence Ontologies
 - Transcriptional Active Genomic Regions
 - Protein-Protein interactions

Genomic Feature Models

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Two genomic feature modeling approaches:

1. one component GBLUP approach (**GBLUP1**)
2. two component GBLUP approach (**GBLUP2**)

- **Test procedures and test statistics used for identifying**
genomic features of interest

One Component GBLUP

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Step 1: Fit a single one component linear mixed model:

$$\mathbf{M}_1: \quad \mathbf{y} = \mathbf{X}\mathbf{b} + \mathbf{Z}\mathbf{g} + \mathbf{e}$$

where \mathbf{g} is the genomic values based on all genetic markers.

Assumptions:

$$\begin{aligned}\mathbf{g} &\sim N(\mathbf{0}, \mathbf{G}\sigma_g^2) \text{ where } \mathbf{G} = (\mathbf{W}\mathbf{W}')/N \\ \mathbf{e} &\sim N(\mathbf{0}, \mathbf{I}\sigma_e^2)\end{aligned}$$

\mathbf{g} and \mathbf{e} are uncorrelated

One Component GBLUP

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Step 2: Backsolve to get single markers effects and test statistics:

$$\hat{\mathbf{s}} = \mathbf{W}'(\mathbf{W}\mathbf{W}')^{-1}\hat{\mathbf{g}}$$

$$t_{\hat{s}_j} = \frac{\hat{s}_j^2}{\text{Var}(\hat{s}_j)}$$

Step 3: For each genomic feature compute a summary statistic based on single marker tests within feature such as:

Sum of all single marker test statistics

$$T_{\text{sum}} = \sum_{i=1}^{n_F} t_i$$

Two Component GBLUP

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Step 1: Fit a two component linear mixed model for each genomic feature:

$$\mathbf{M}_2: \quad \mathbf{y} = \mathbf{X}\mathbf{b} + \mathbf{Z}\mathbf{q}_f + \mathbf{Z}\mathbf{q} + \mathbf{e}$$

where \mathbf{q}_f is the **genomic values for the feature of interest** and \mathbf{q} is the genomic values based on all genetic markers.

Assumptions:

$$\begin{aligned}\mathbf{q} &\sim N(0, \mathbf{G}\sigma_g^2) & \mathbf{G} &= (\mathbf{W}\mathbf{W}')/N \\ \mathbf{q}_f &\sim N(0, \mathbf{G}_f\sigma_{g_f}^2) & \mathbf{G}_f &= (\mathbf{W}_f\mathbf{W}_f')/N_f \\ \mathbf{e} &\sim N(0, \mathbf{I}\sigma_e^2)\end{aligned}$$

\mathbf{q}_f , \mathbf{q} , and \mathbf{e} are uncorrelated

Two Component GBLUP

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Step 2: For each genomic feature test significance using:

Likelihood ratio test:

$$T_{LRT} = -2[\ell(\hat{\Theta}_1|y) - \ell(\hat{\Theta}_2|y)] \quad (\mathcal{M}_1 \leftrightarrow \mathcal{M}_2)$$

Score test:

$$T_{Score} = 0.5(y - \hat{\mathbf{x}}\hat{\mathbf{b}}_1)' \hat{\mathbf{V}}_1^{-1} Z \mathbf{G}_f Z' \hat{\mathbf{V}}_1^{-1} (y - \hat{\mathbf{x}}\hat{\mathbf{b}}_1) \quad (\mathcal{M}_1)$$

Goeman et al. 2004

Two Component GBLUP

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Cross validation procedure for each genomic feature:

- 80% training / 20% validation
- 20 randomly chosen data sets

Step 1: Fit two component GBLUP and compute the total genomic values, $\mathbf{g}_t = \mathbf{g}_f + \mathbf{g}_e$ for the individuals in validation data set

Step 2: Compute correlation between the total genomic values obtained from step 1 and from the analysis using all data

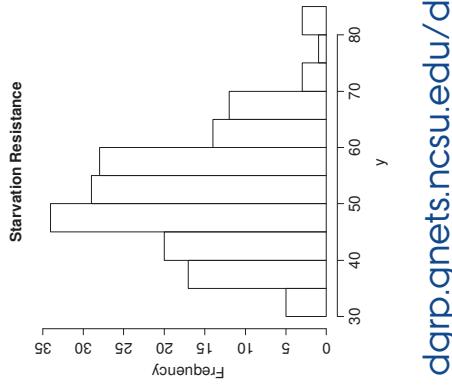
Step 3: Compute predictive ability (PA) of the model as the average of the correlations across all validation subsets.

DGRP Data

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- **168 inbred lines** from the DGRP population
 - derived from 20 generations of full sib mating
- **Whole Genome Sequence data**
 - 2.5M SNPs
 - 20.89 SNP pr Kb
- **Starvation Resistance:** a measure of how long time it takes before a fly dies due to food deprivation
 - 17,324 phenotypic observations
 - on average 104 observation pr line (47-216)
 - high between line variation ($h^2 = 0.39$)



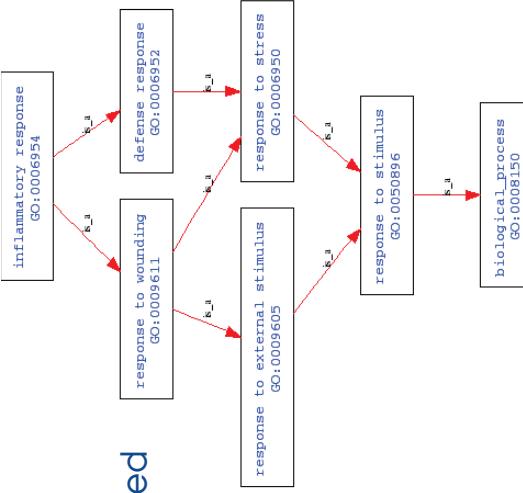
dgrp.gnets.ncsu.edu/data

Genomic Features

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Genomic Features defined by Gene Ontology (GO)

Gene grouped according to biological processes such as mitosis or immune response, that are accomplished by ordered assemblies of molecular functions

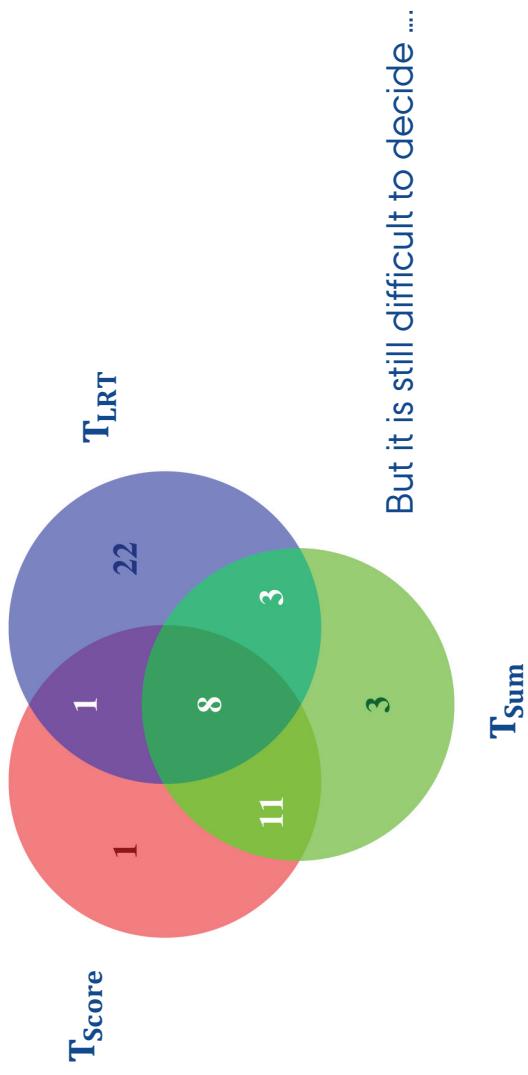


- map SNP to Gene to GO
- 5kb up-/down-stream of gene
- 2066 SNP sets (genomic features)

Results

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Large overlap among the significant genomic features based on summary statistics from **GBLUP1** and **GBLUP2**



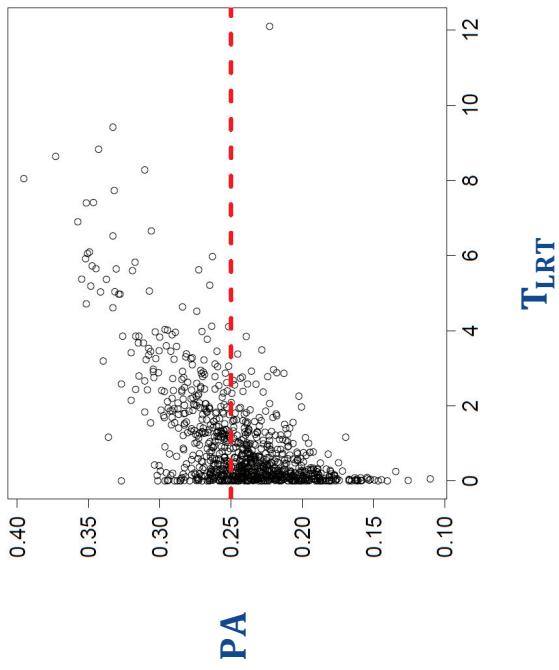
Results

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Higher LRT is linked to higher PA:

$$\mathbf{y} = \mathbf{X}\mathbf{b} + \mathbf{Z}\mathbf{q}_f + \mathbf{Z}\mathbf{q} + \boldsymbol{\epsilon}$$



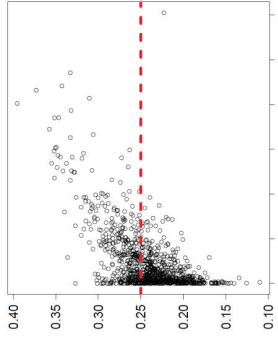
Results

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Rank correlation between PA and -logP of summary statistics

GBLUP1
 T_{Sum} : 0.50

GBLUP2
 T_{LRF} : 0.52
 T_{Score} : 0.37



Results

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High ranking genomic features defined by gene ontologies

GO	PA	LR	H ²	N _f
GO:0007474	0.395	8.05	84.8%	29,018
GO:0042742	0.373	8.64	50.5%	6,225
GO:0007464	0.357	6.90	48.2%	14,263
GO:0048747	0.355	5.38	25.5%	5,256
GO:0048103	0.352	5.92	33.6%	2,468
GO:0007465	0.352	4.72	31.2%	5,541
GO:0045893	0.351	7.40	69.0%	24,874
GO:0007458	0.350	6.05	38.7%	3,739
GO:0008587	0.349	6.10	61.3%	16,124
GO:0010389	0.348	5.19	19.1%	682

explain a **larger proportion of genomic variance**, provide **better model fit or predictive ability** for starvation resistance in DRGP

Novel Insights?

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Biological interpretation is difficult ... BUT high ranking genomic features:

- are associated with genes involved in growth and development (increased developmental time seems to be evolutionary important in populations that have elevated starvation resistance) (Rion and Kawecki, 2007)
- are associated with genes involved in immune system (immune response is costly and lines with a down regulated immune response might have more resources available for energy storage, and could thereby resist starvation for longer periods) (Lochmiller and Deerenberg, 2000)
- are associated with genes whose expression levels are associated to starvation resistance (Ayroles et al., 2009)

Conclusion

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Genomic feature model analysis can be used to reveal biological relevant classification schemes that:

- **explain the higher proportions of genomic variances**
- **provide better model fit**
- **increase predictive ability of the statistical model**

Conclusion

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A number of genomic feature model approaches are available and can easily be implemented using standard linear mixed modeling methods:

- **One component GBLUP approach** is computational fast and the significant associated genomic features are similar to the ones obtained from two component GBLUP approach
- **Two component GBLUP approach** more computational demanding, but allow us to use the predictive ability associated to the genomic feature as a measure of importance

Acknowledgements

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