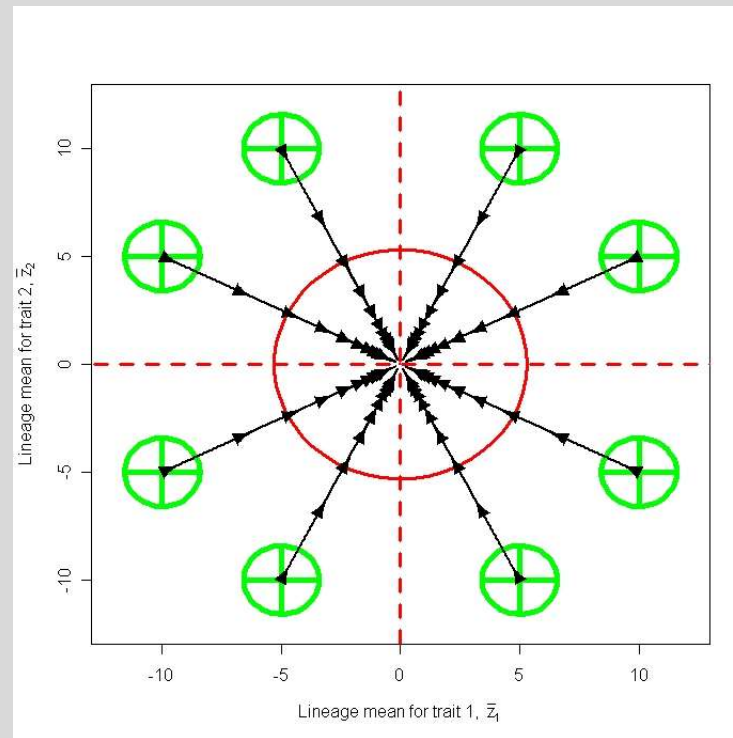


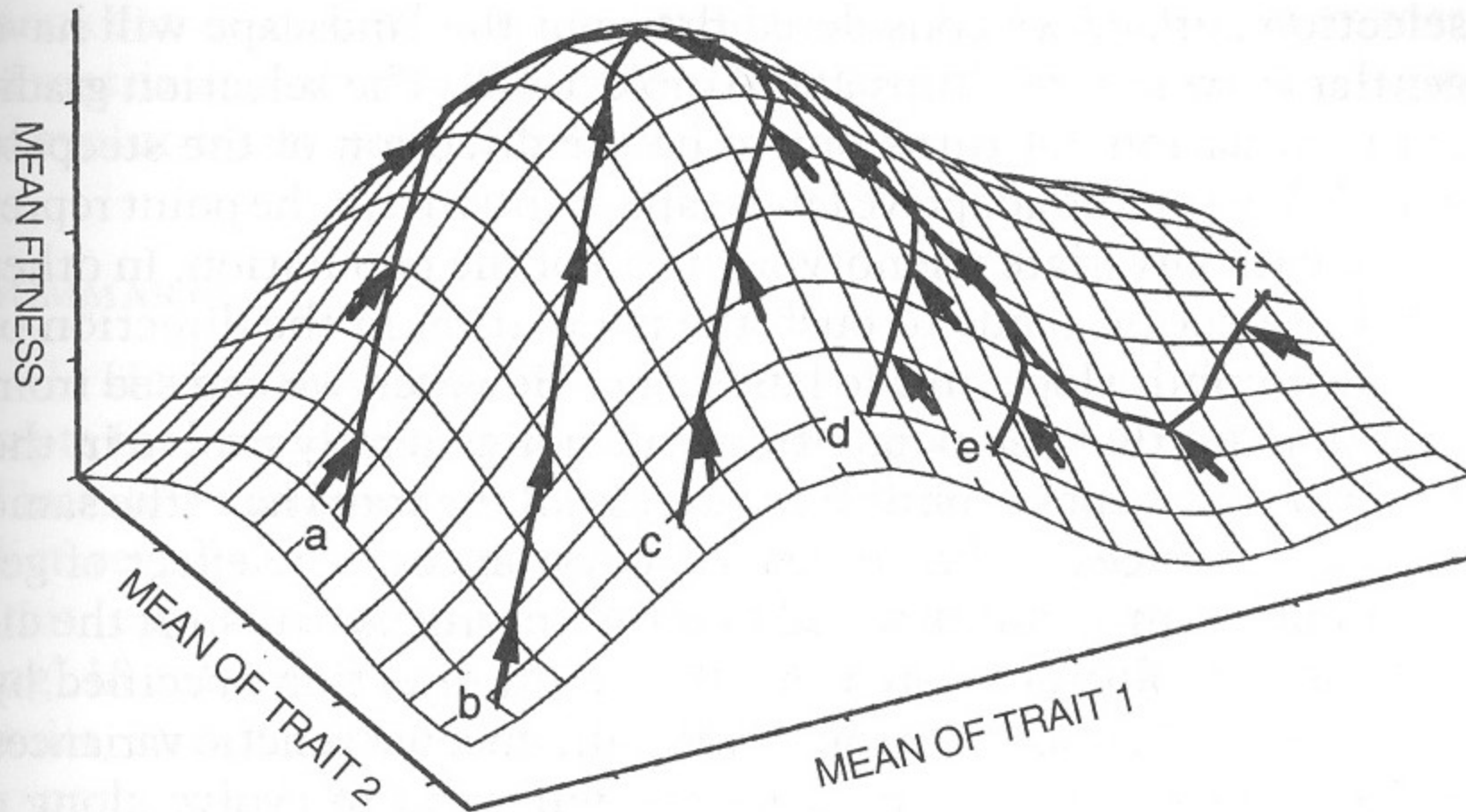
2.3 Selection and Evolution on a Surface



Stevan J. Arnold

Department of Integrative Biology
Oregon State University

Evolution of the trait mean on an adaptive landscape: more than a metaphor



Three Parts

1. Selection on single & multiple traits
2. Selection on a surface
3. Evolution on adaptive landscapes

Part 1. Selection on a Single & Multiple Traits

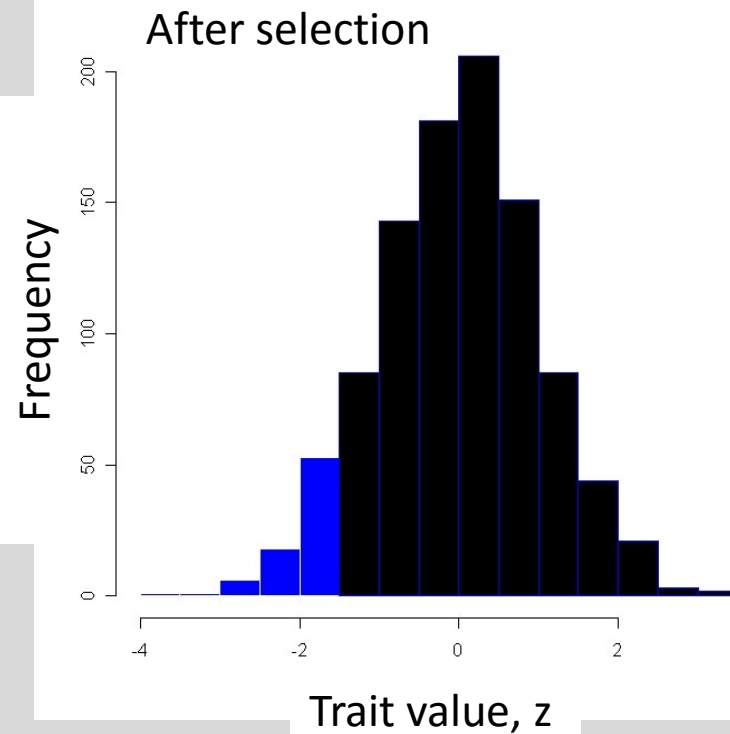
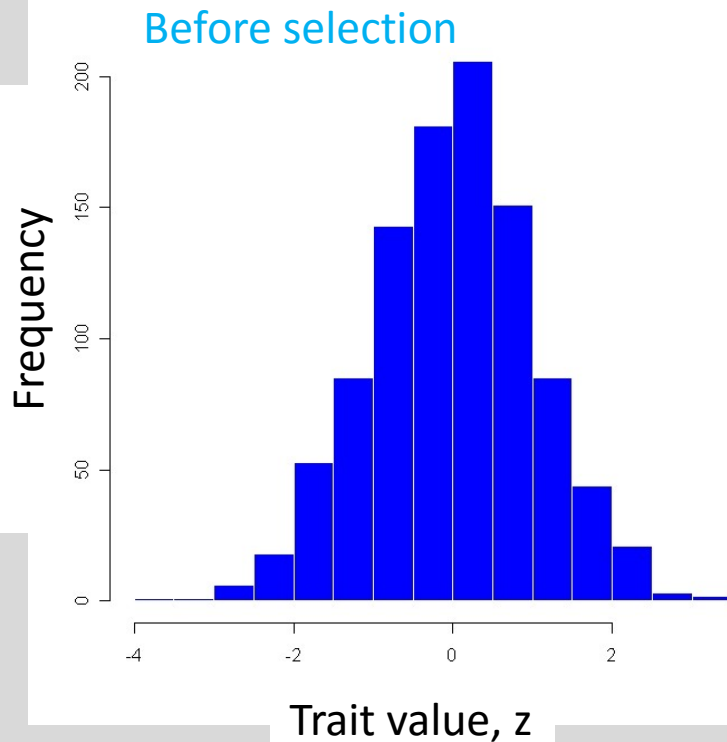


Thesis

- Selection changes trait distributions.
- The contrast between distributions before and after selection provides a powerful description of the force of selection.
- Multivariate measures of selection can correct for the effects of correlations between traits.

1. Selection changes the univariate trait distribution

a. The contrast between distributions before and after selection is particularly revealing



2. Shift in the trait mean, the linear selection differential, s

a. A particular example

$$s = \bar{z}^* - \bar{z} = 0.16 - (-0.01) = 0.17$$

b. The general case

$$\bar{z} = \int p(z) z dz$$

where $p(z)$ is trait frequency before selection

$$\bar{z}^* = \int p(z)^* z dz$$

where $p(z)^*$ is trait frequency after selection

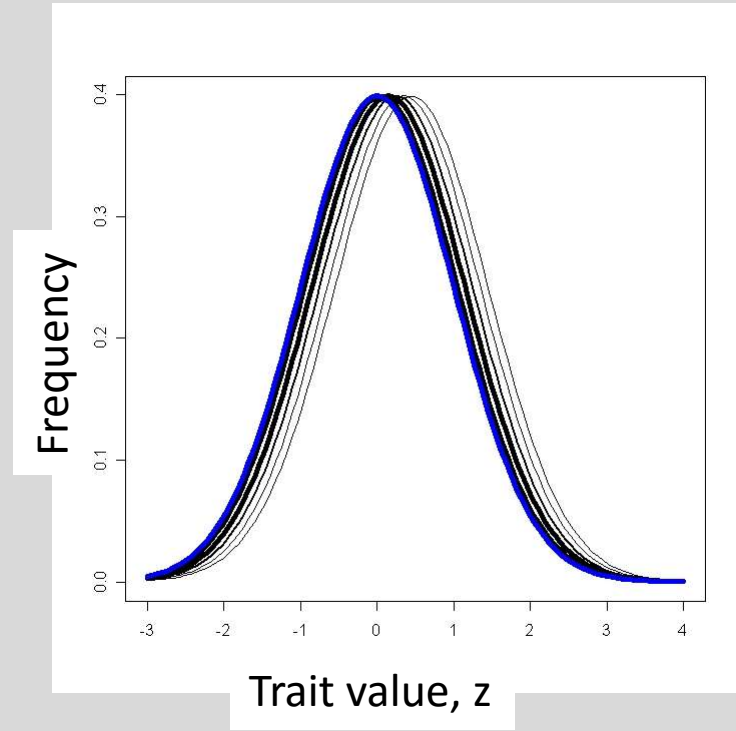
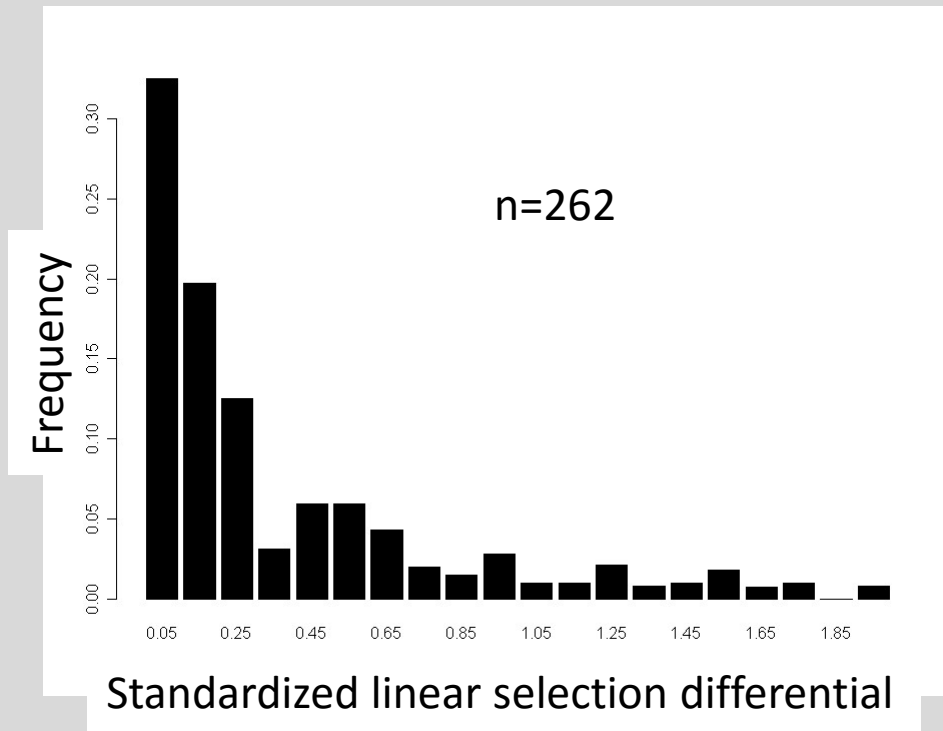
$$p(z)^* = w(z)p(z)$$

where $w(z)$ is relative fitness of the z trait class

3. Examples and Surveys of selection differentials

a. The standardized linear selection differential, s'

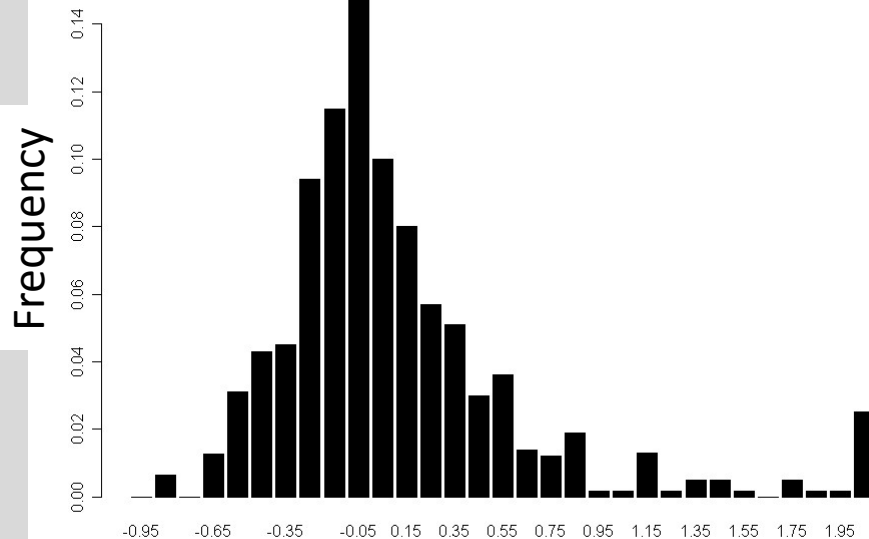
$$s' = (\bar{z}^* - \bar{z})/\sqrt{P}$$



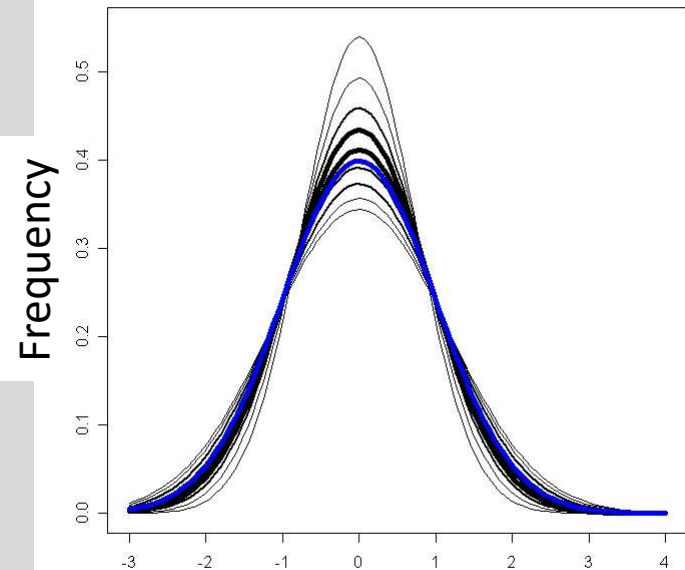
3. Examples and Surveys of selection differentials

b. The standardized nonlinear selection differential, C'

$$C' = (P^* - P + s^2)/P$$



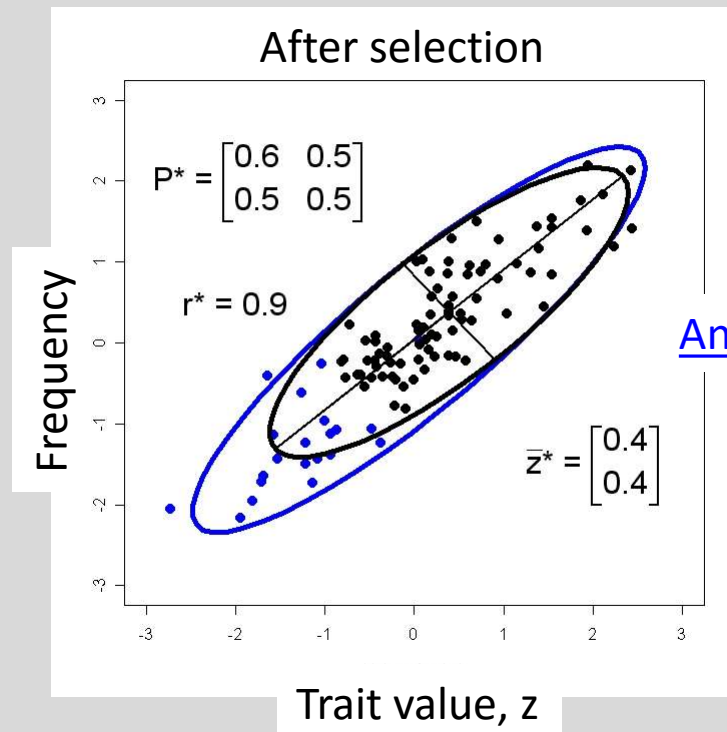
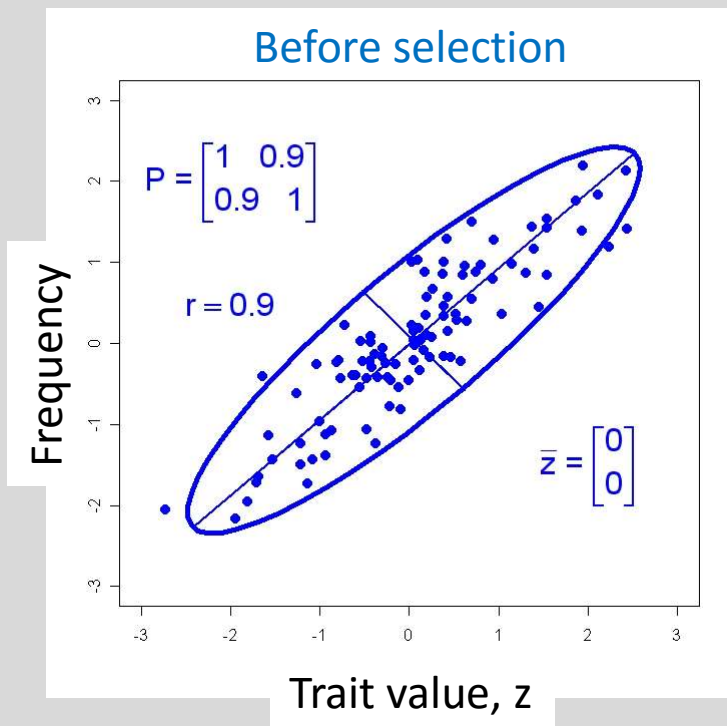
Standardized nonlinear selection differential



Trait value, z

4. Selection changes the multivariate trait distribution

a. The contrast between distributions before and after selection

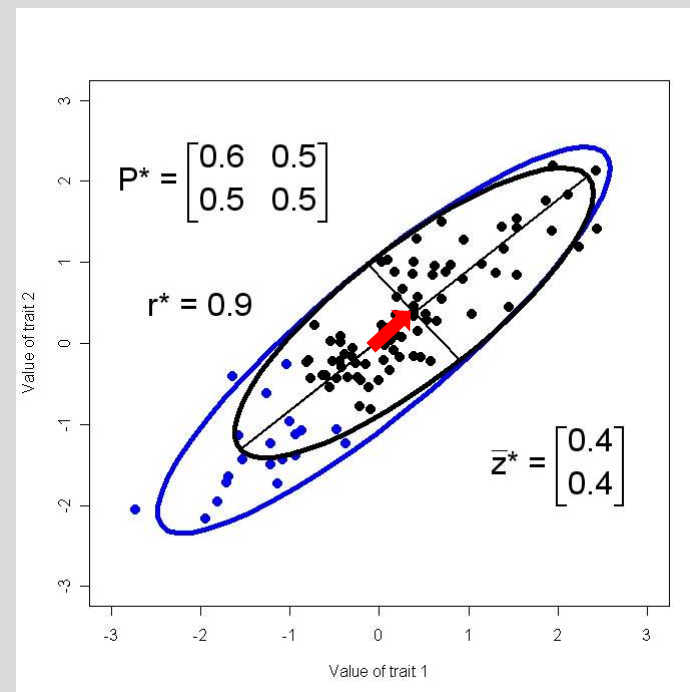
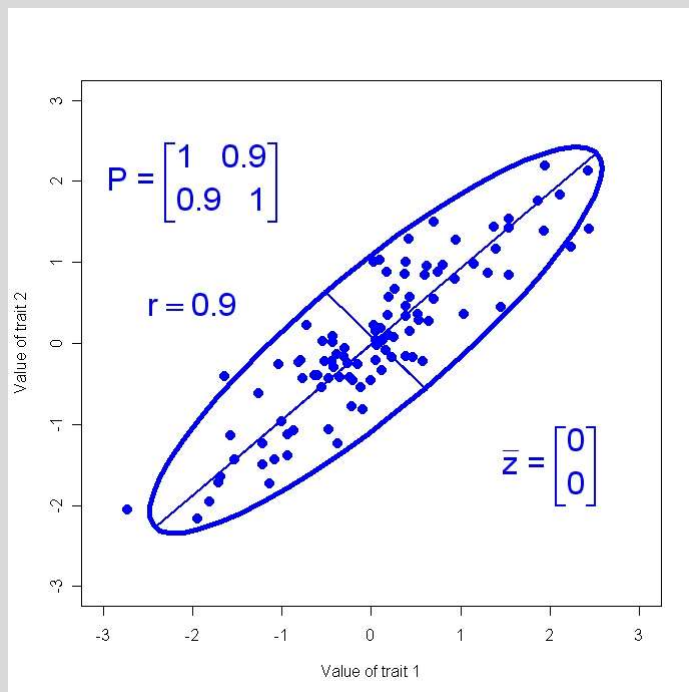


[Animation2](#)

4. Selection changes the multivariate trait distribution

b. The directional selection differential, \mathbf{s} , is a vector

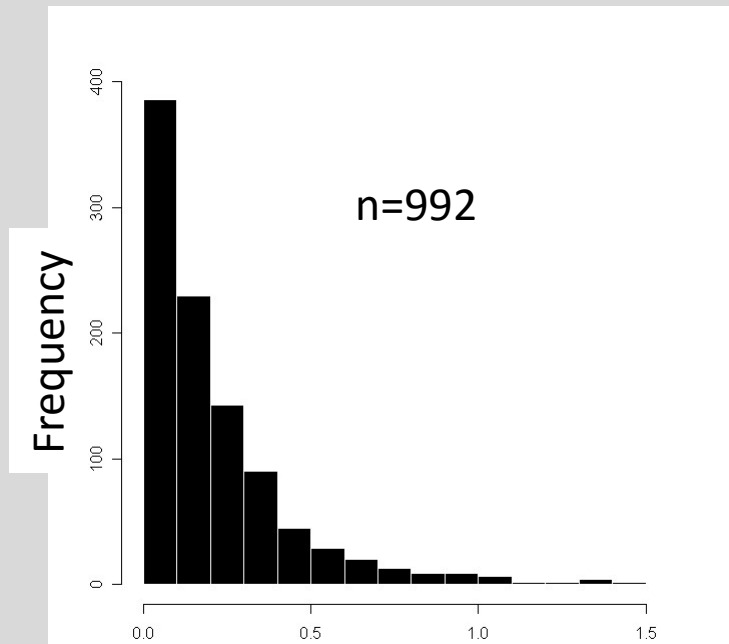
$$\mathbf{s} = \text{Cov}(\mathbf{w}, \mathbf{z}) = \begin{bmatrix} \text{Cov}(w, z_1) \\ \text{Cov}(w, z_2) \end{bmatrix} = \bar{\mathbf{z}} - \bar{\mathbf{z}}^* = \begin{bmatrix} \bar{z}_1 - \bar{z}_1^* \\ \bar{z}_2 - \bar{z}_2^* \end{bmatrix} = \begin{bmatrix} s_1 \\ s_2 \end{bmatrix}$$



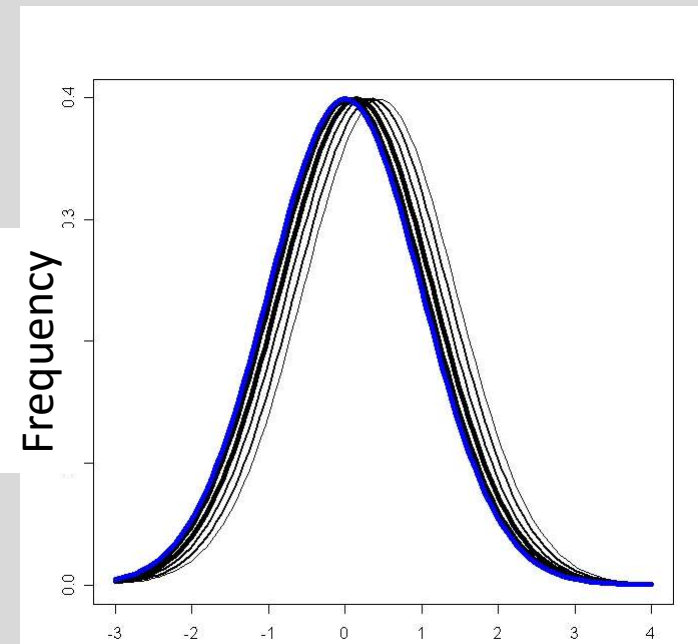
5. Survey

Standardized directional selection gradients, β

$$\beta \equiv P^{-1}s$$



Standardized directional selection gradient

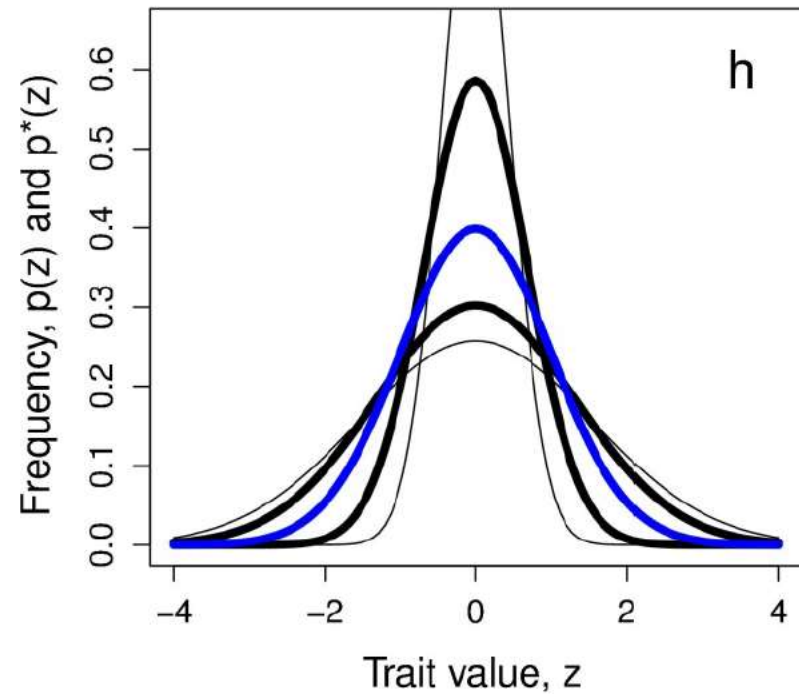
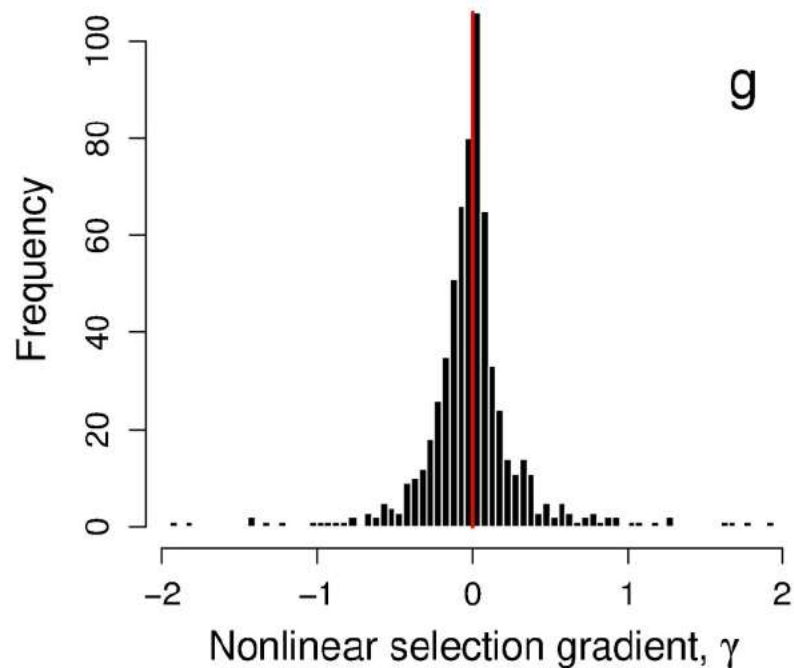


Trait value, z

5. Survey, continued

Standardized nonlinear selection gradients, γ

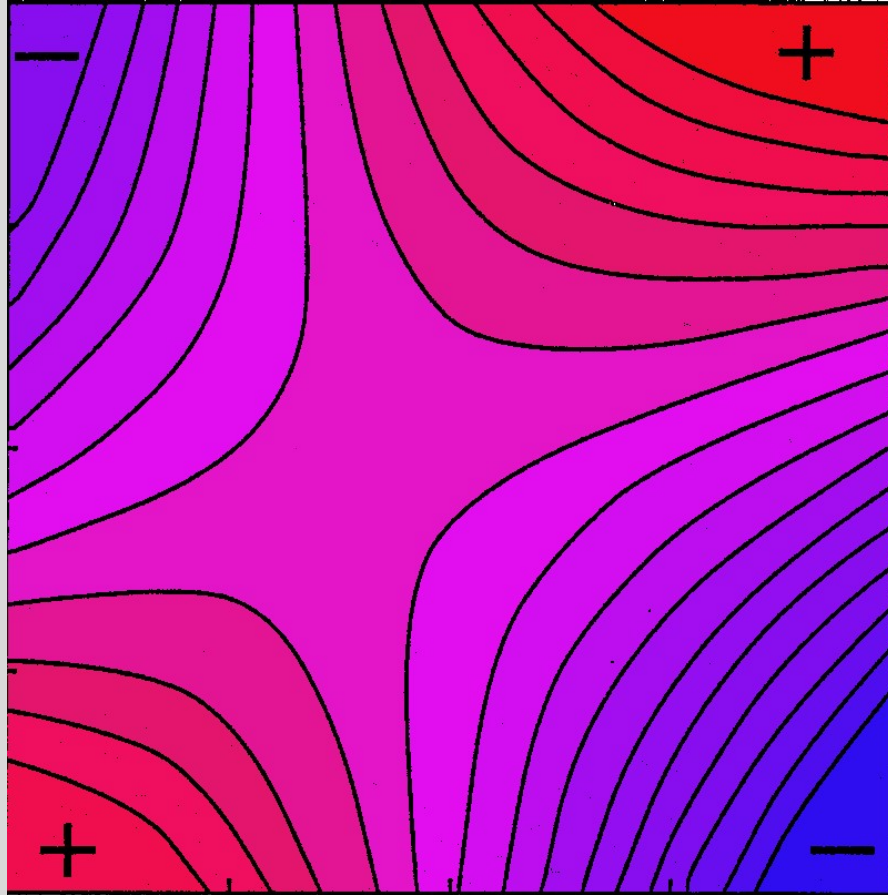
$$\gamma \equiv P^{-1}CP^{-1}$$



What have we learned?

1. The change in trait distributions before and after selection within a generation can be used to derive useful measures of selection.
2. Using those measures we can distinguish between the effects of directional and stabilizing selection.
3. We can also distinguish between the direct and indirect effects of selection mediated by correlations between traits.

Part 2. Selection as a Surface



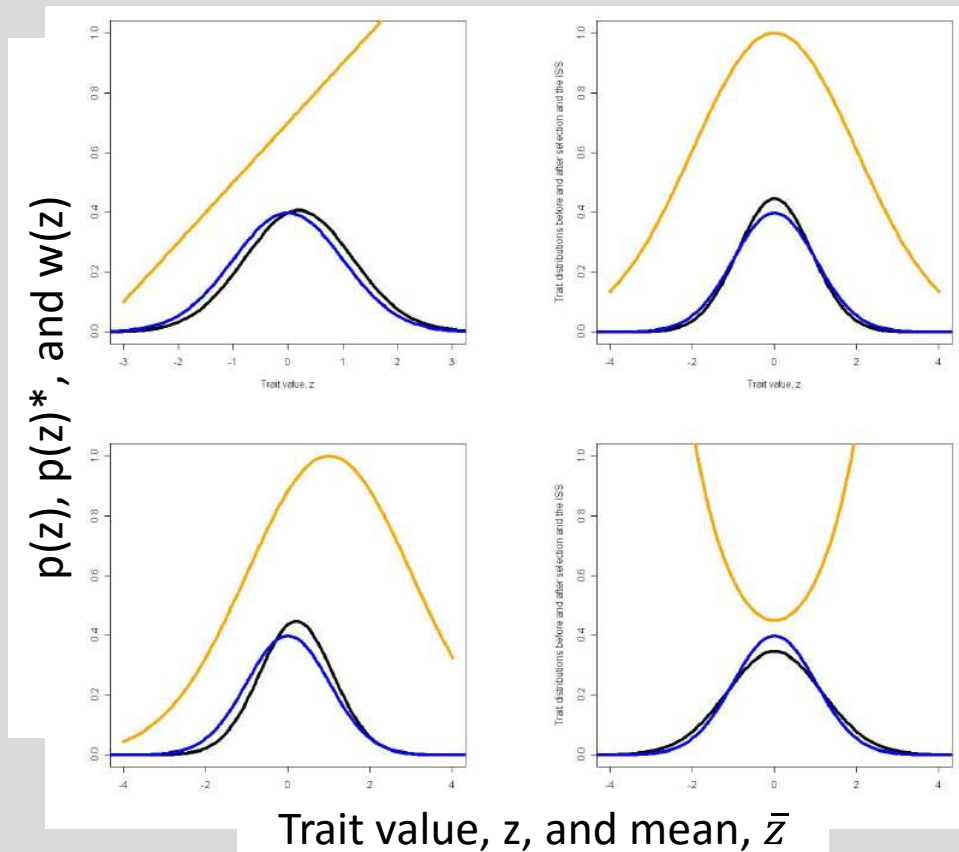
Thesis

- We can think of selection as a surface.
- Selection surfaces allow us to estimate selection parameters, as well as visualize selection.
- To visualize and estimate, we need to keep track of three kinds of surfaces:
 1. the individual selection surface
 2. our approximation of that surface
 3. the adaptive landscape.

1. The Individual Selection Surface

Expected individual fitness, $w(z)$, as a function of trait value, z

- a. A model for how selection that changes trait means and variances



[Animation 0](#)

2. Approximations to the univariate ISS

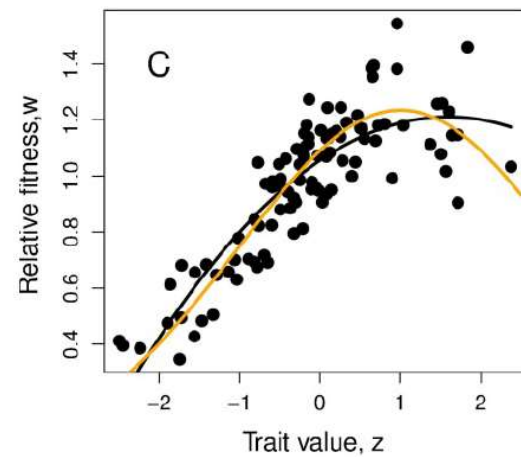
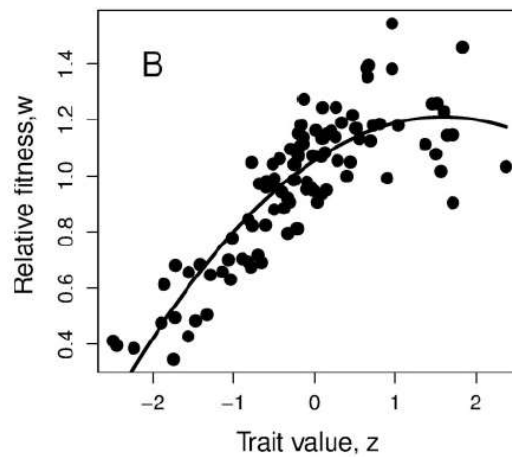
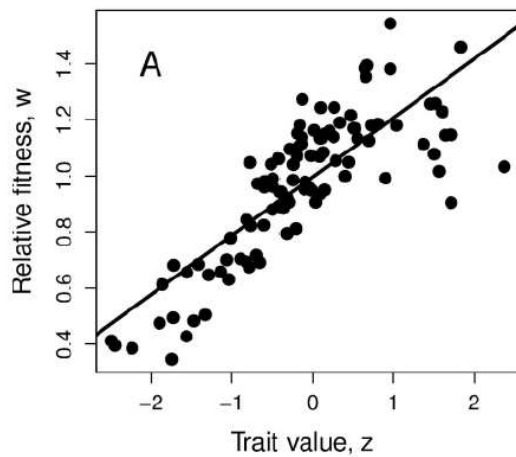
Linear & quadratic approximations:
a way to estimate β and γ

$$w(z) = \alpha + \beta z + \varepsilon \quad \text{linear}$$

$$w(z) = \alpha + \beta z + \frac{1}{2} \gamma z^2 + \varepsilon \quad \text{quadratic*}$$

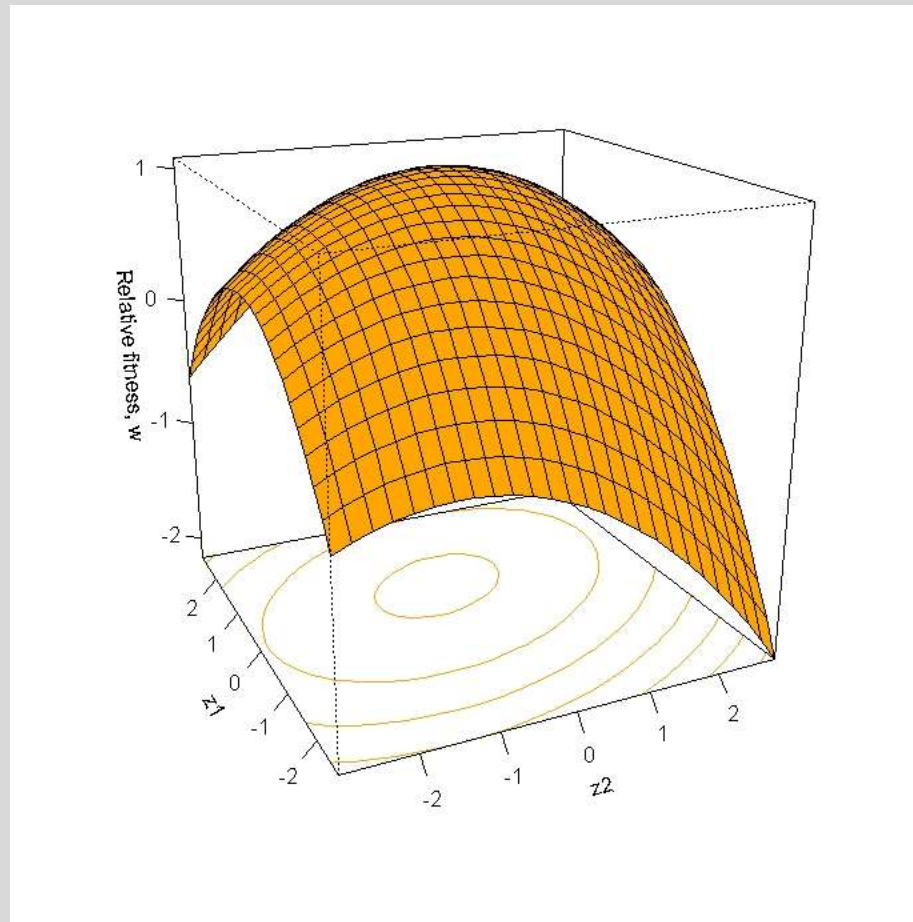
* the factor of $\frac{1}{2}$ makes γ a second derivative

2. Linear and quadratic approximations to a Gaussian ISS



3. The multivariate individual selection surface, *ISS*

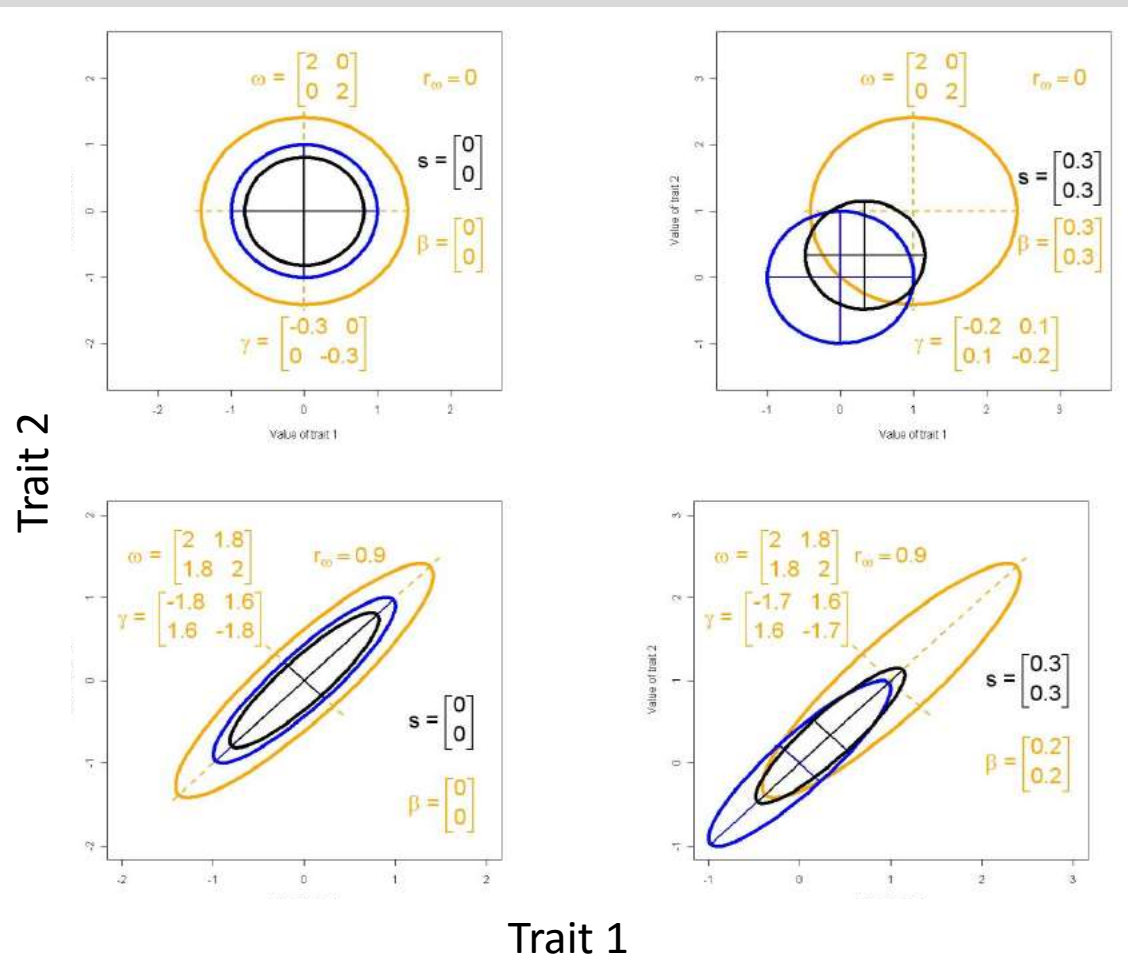
a. A hypothetical bivariate example



[Animation 3](#)

3. The multivariate individual selection surface, ISS

b. Some examples of bivariate ISSs and the selection they impose



[Animation 4](#)

4. Approximations to the multivariate ISS

a. Linear and quadratic approximations, a way to estimate β and γ

For simplicity, we consider the two-trait case

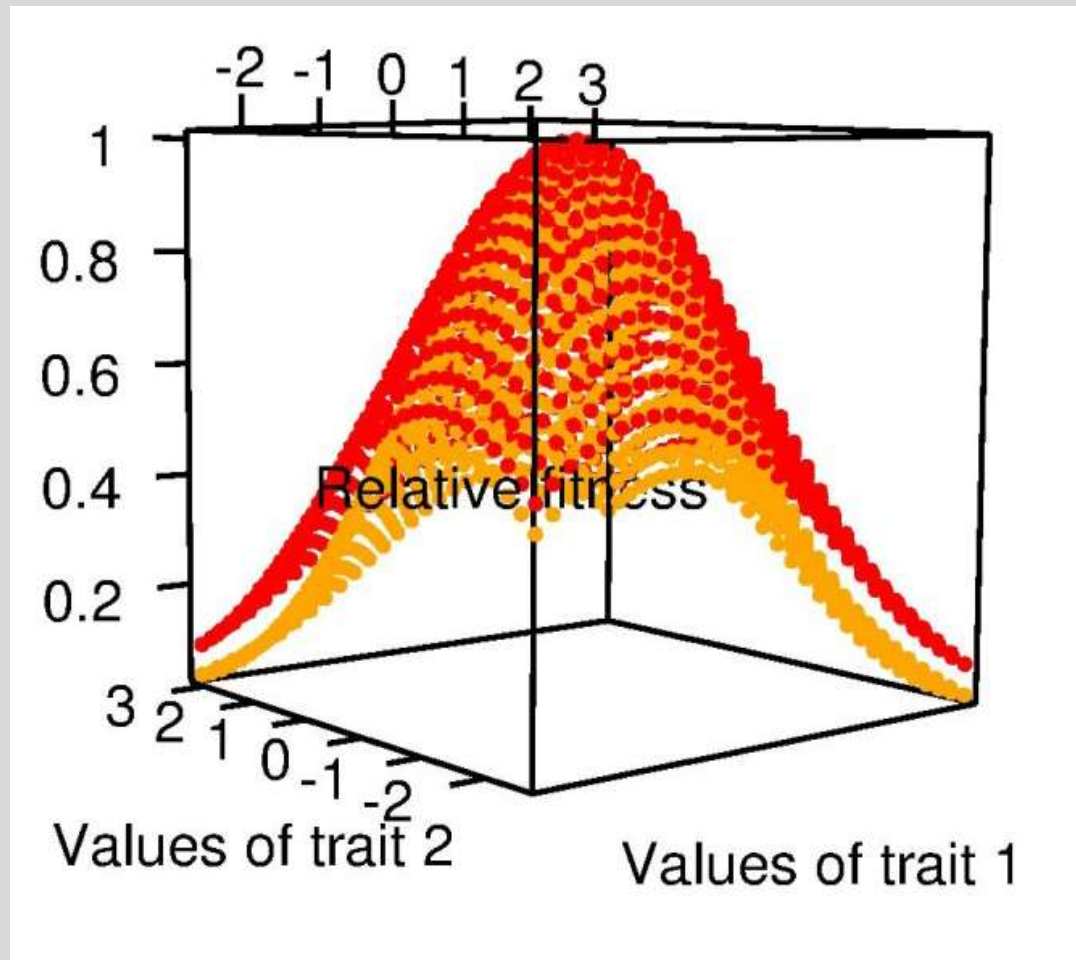
Linear approximation

$$w(\mathbf{z}) = \alpha + \beta^T \mathbf{z} + \varepsilon = \alpha + \beta_1 z_1 + \beta_2 z_2 + \varepsilon$$

Quadratic approximation

$$w(\mathbf{z}) = \alpha + \beta^T \mathbf{z} + \frac{1}{2} \mathbf{z}^T \boldsymbol{\gamma} \mathbf{z} + \varepsilon = \alpha + \beta_1 z_1 + \beta_2 z_2 + \frac{1}{2} \gamma_{11} z_1^2 + \frac{1}{2} \gamma_{22} z_2^2 + \gamma_{12} z_1 z_2 + \varepsilon$$

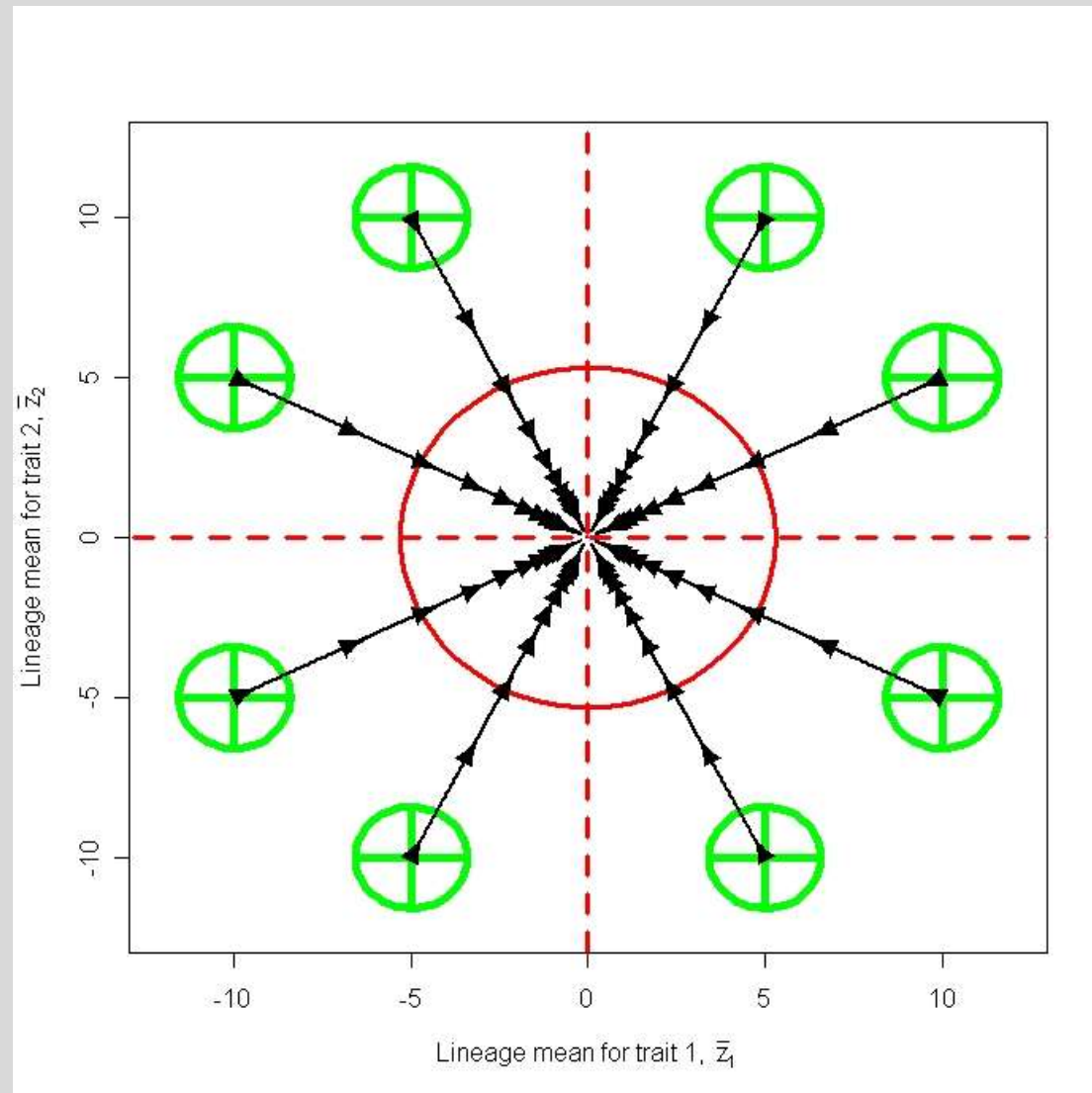
5. The adaptive landscape has less curvature than its ISS



What have we learned?

1. Selection can be described with surfaces.
2. Some approximations of selection surfaces allow us to estimate key measures of selection (β and y).
3. Those key measures in turn tell us about the adaptive landscape.

Evolution on Adaptive Landscapes



Thesis

- Models for adaptive radiation can be constructed with quantitative genetic parameters.
- The use of quantitative genetic parameters allows us to cross-check with the empirical literature on inheritance, selection, and population size.
- Stabilizing selection and peak movement appear to be necessary but may not be sufficient to account for evolution in deep time.

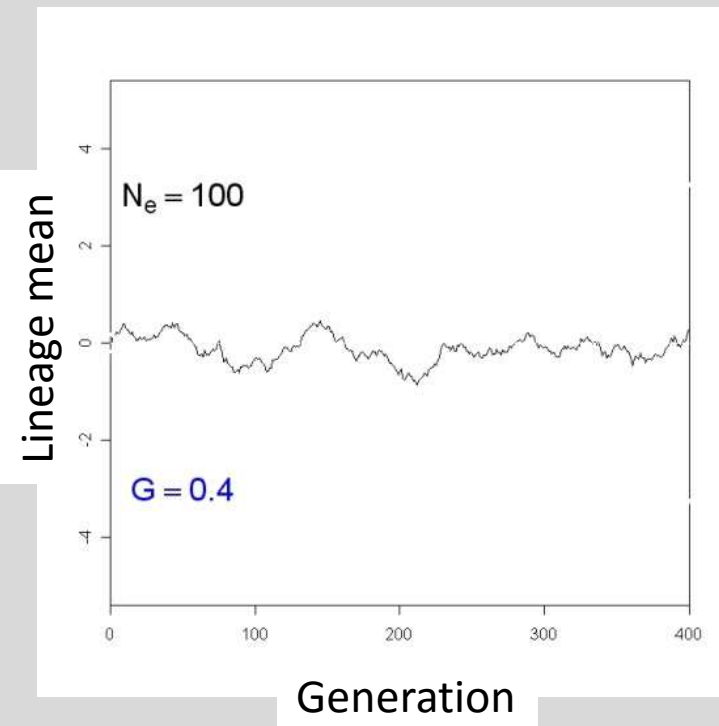
1. Evolution without selection, genetic drift

- a. Sampling N_e individuals from a normal distribution of breeding values

$$Var(\bar{z}) = \frac{1}{N_e} G$$

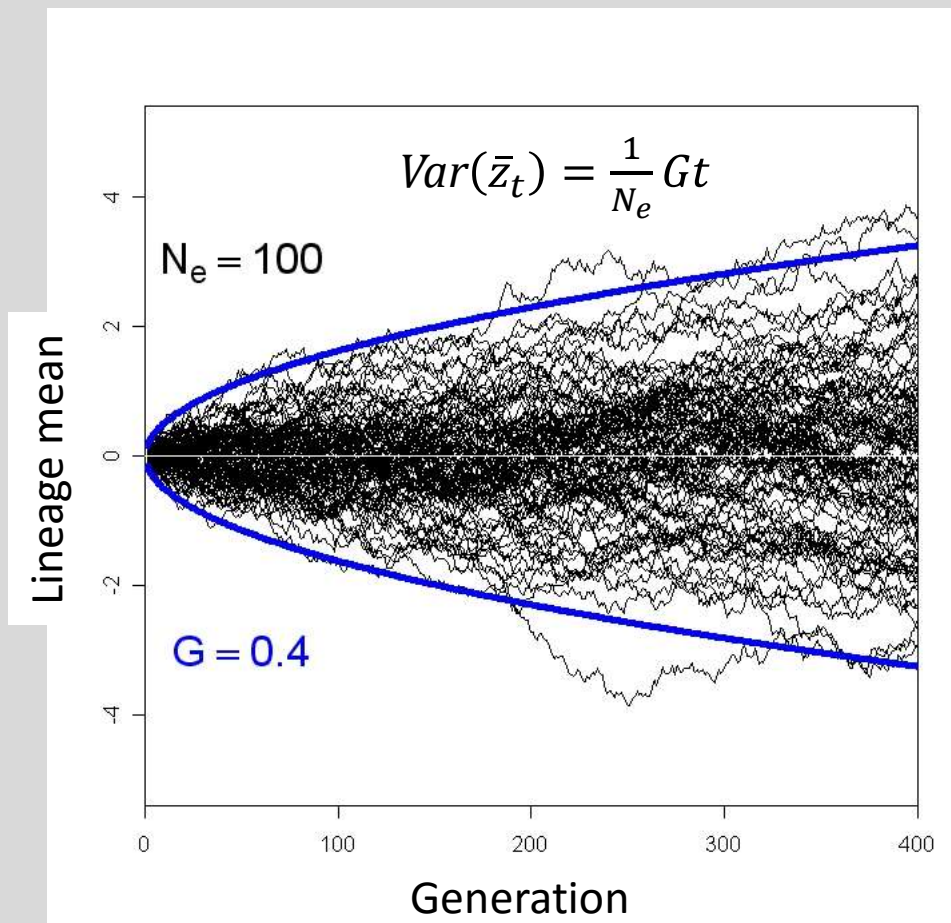
- b. Projecting the distribution of breeding values into the future

$$Var(\bar{z}_t) = \frac{1}{N_e} Gt$$



1. Evolution without selection, genetic drift

c. Many replicate populations evolving by drift



[Animation 1](#)

2. Univariate evolution about a stationary peak

a. Tendency to evolve uphill on the adaptive landscape

$$\Delta \bar{z} = G\beta = G \frac{\partial \ln \bar{W}}{\partial \bar{z}}$$

$$\Delta \ln \bar{W} \cong \Delta \bar{z}^T G^{-1} \Delta \bar{z} \geq 0$$

b. Stochastic dynamics with a single Gaussian, stationary peak

The Ornstein-Uhlenbeck, OU, process

Per generation change in mean

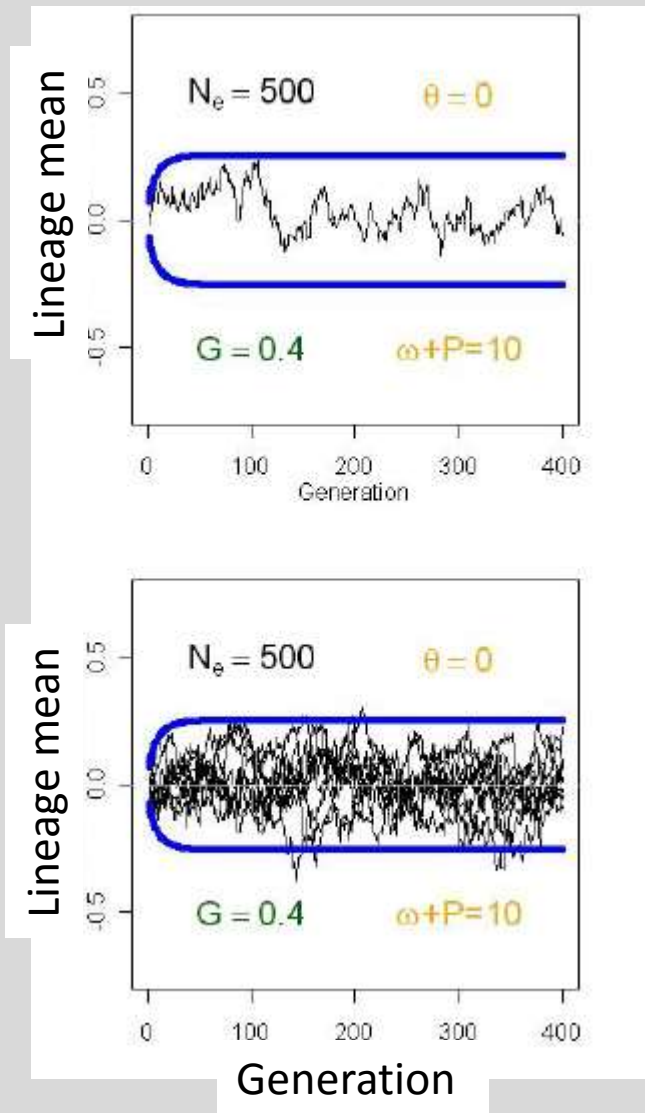
$$\bar{z}(t+1) = \bar{z}(t) + G \frac{[\theta - \bar{z}(t)]}{\omega + P} + N(0, G / N_e)$$

Variance among replicate lineages in trait mean

$$Var(\bar{z}_t) = \frac{\omega + P}{2N_e} \left\{ 1 - \exp \left[-2 \left(\frac{G}{\omega + P} \right) t \right] \right\}$$

2. Univariate evolution about a stationary peak

b. Stochastic dynamics with a single, stationary peak



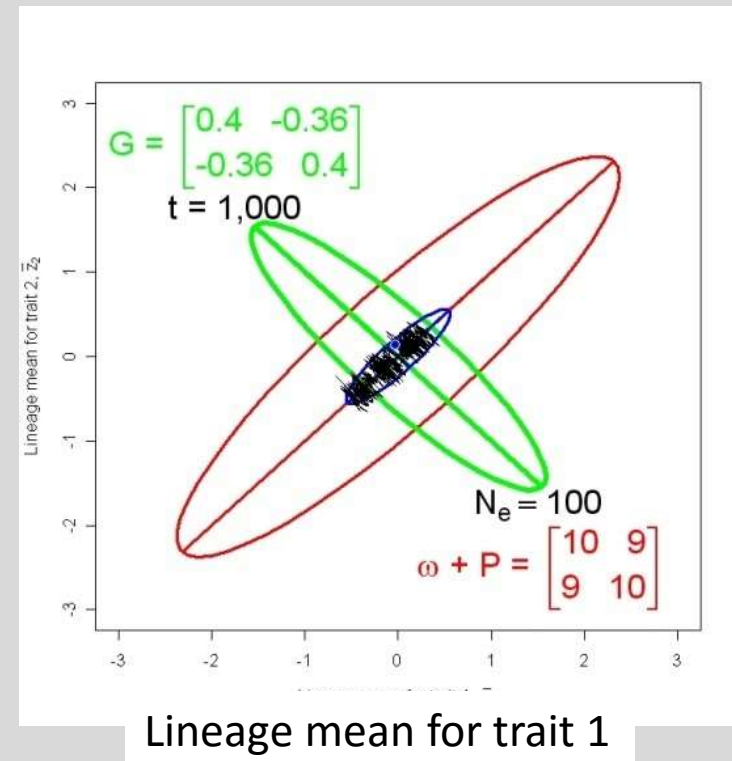
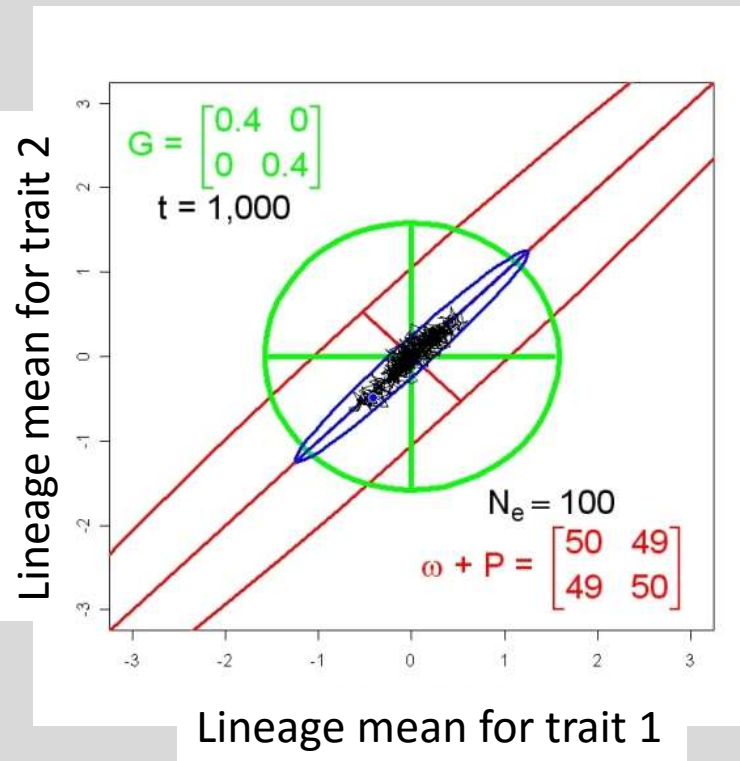
[Animation 2](#)

3. Bivariate evolution about a stationary peak

Replicate responses to a single Gaussian, stationary peak

The adaptive landscape trumps the G -matrix

$$\text{Var}(\bar{z}_t) = \frac{(\omega + P)}{2N_e} \left\{ 1 - \exp \left[-2tG(\omega + P)^{-1} \right] \right\}.$$

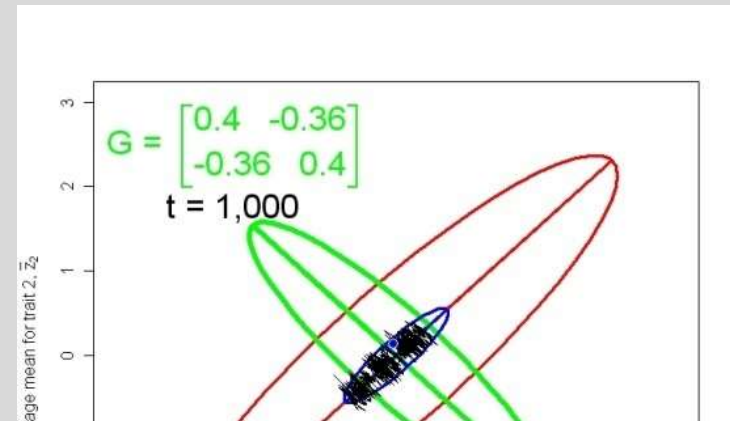
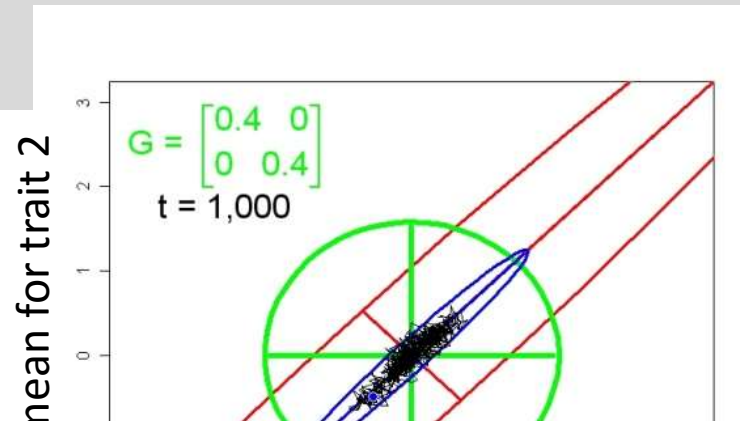


3. Bivariate evolution about a stationary peak

Stochastic response to a single Gaussian, stationary peak

The adaptive landscape trumps the G -matrix

$$\text{Var}(\bar{z}_t) = \frac{(\omega + P)}{2N_e} \left\{ 1 - \exp \left[-2tG(\omega + P)^{-1} \right] \right\}.$$



The heartbreak of OU: to account for data, requires small N_e or very weak stabilizing selection (large ω)

Lineage mean for trait 1

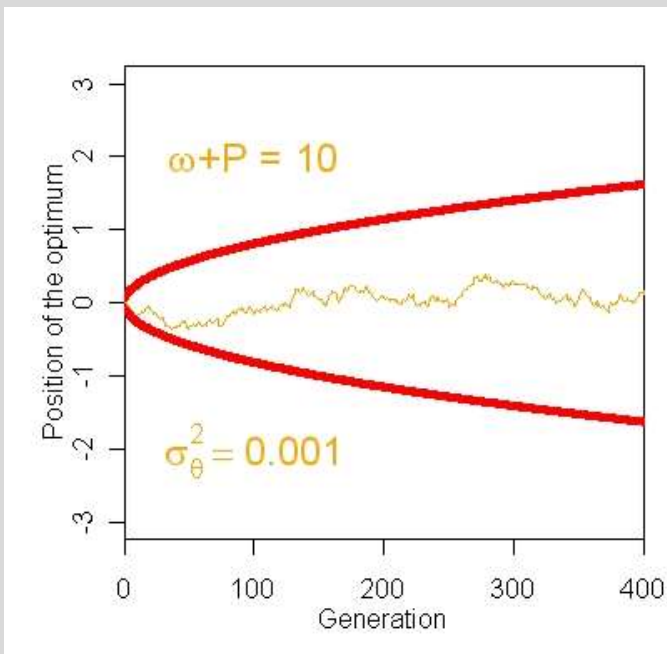
Lineage mean for trait 1

4. Evolution when the peak moves

a. Brownian motion of a Gaussian adaptive peak

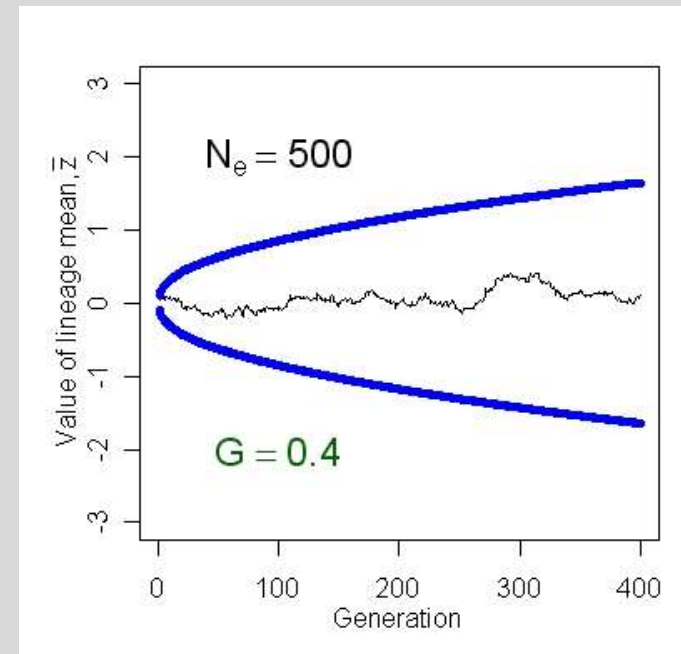
$$\theta_{t+1} = \theta_t + \varepsilon_\theta$$

The optimum, θ , undergoes Brownian motion



$$\Delta \bar{z}(t+1) = \left(\frac{\theta_t - \bar{z}_t}{\omega + P} \right) G + N(0, G / N_e)$$

The lineage mean chases the optimum



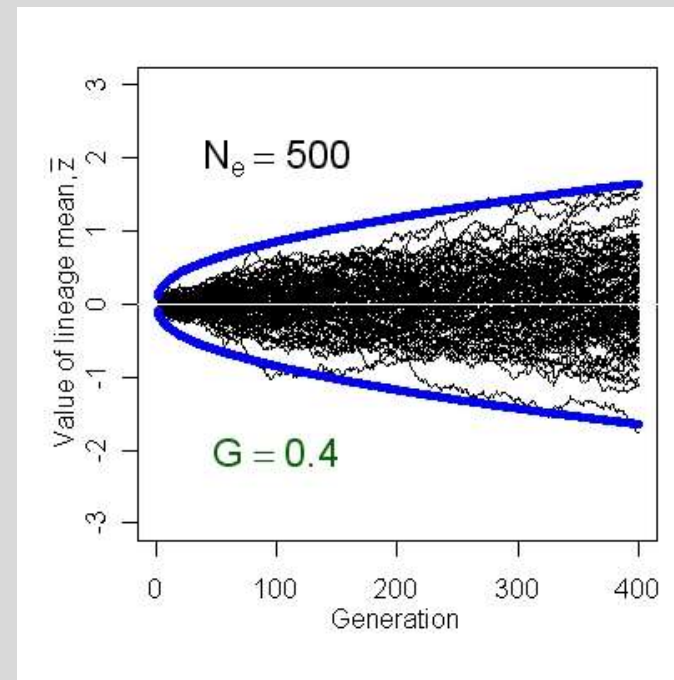
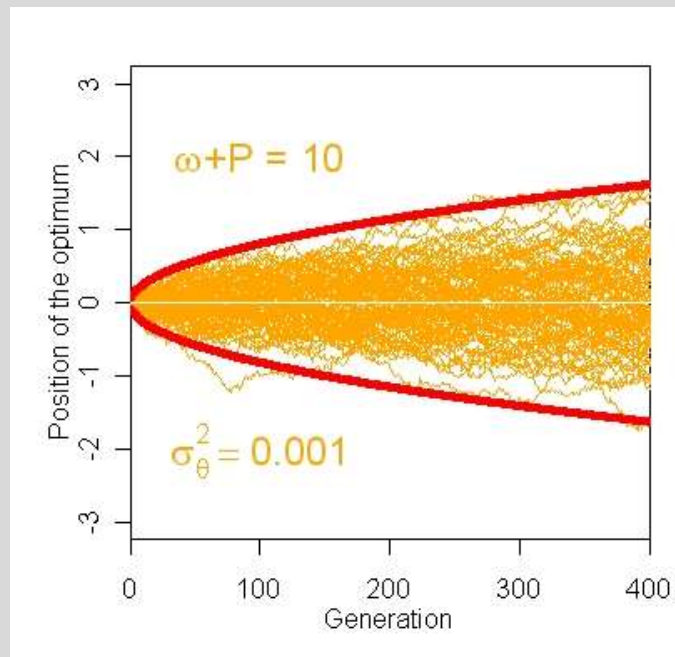
4. Evolution when the peak moves

a. Brownian motion of a Gaussian adaptive peak

Replicate lineages respond to replicate peak movement

$$\text{Var}[\bar{z}(t)] = \frac{\sigma_{\theta}^2 + \frac{G}{N_e}}{2a} \{1 - \exp[-2at]\} + \sigma_{\theta}^2 t \left\{ 1 - 2 \frac{(1 - \exp[-at])}{at} \right\}$$

$$a = \frac{G}{\omega + P}$$

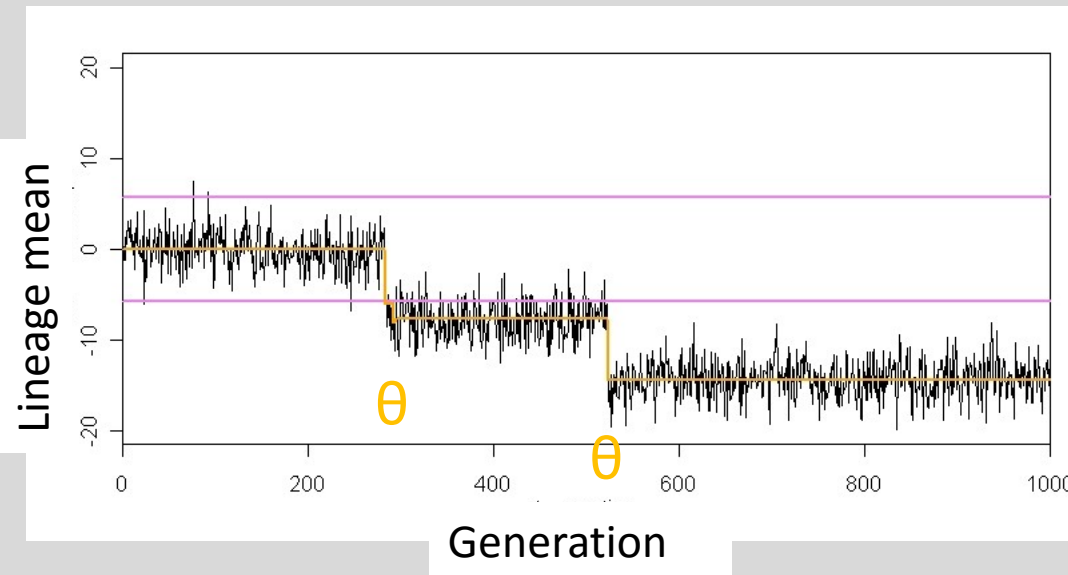


4. Evolution when the peak moves

b. Multiple burst model of peak movement

The optimum, θ , moves in rare bursts, governed by a Poisson process, but is otherwise stationary

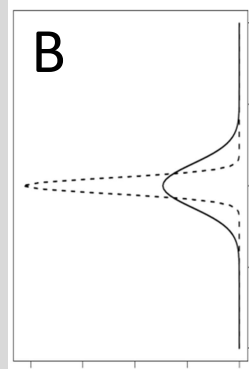
The lineage mean instantaneously tracks bursts in the optimum, but otherwise evolves according to a white noise process



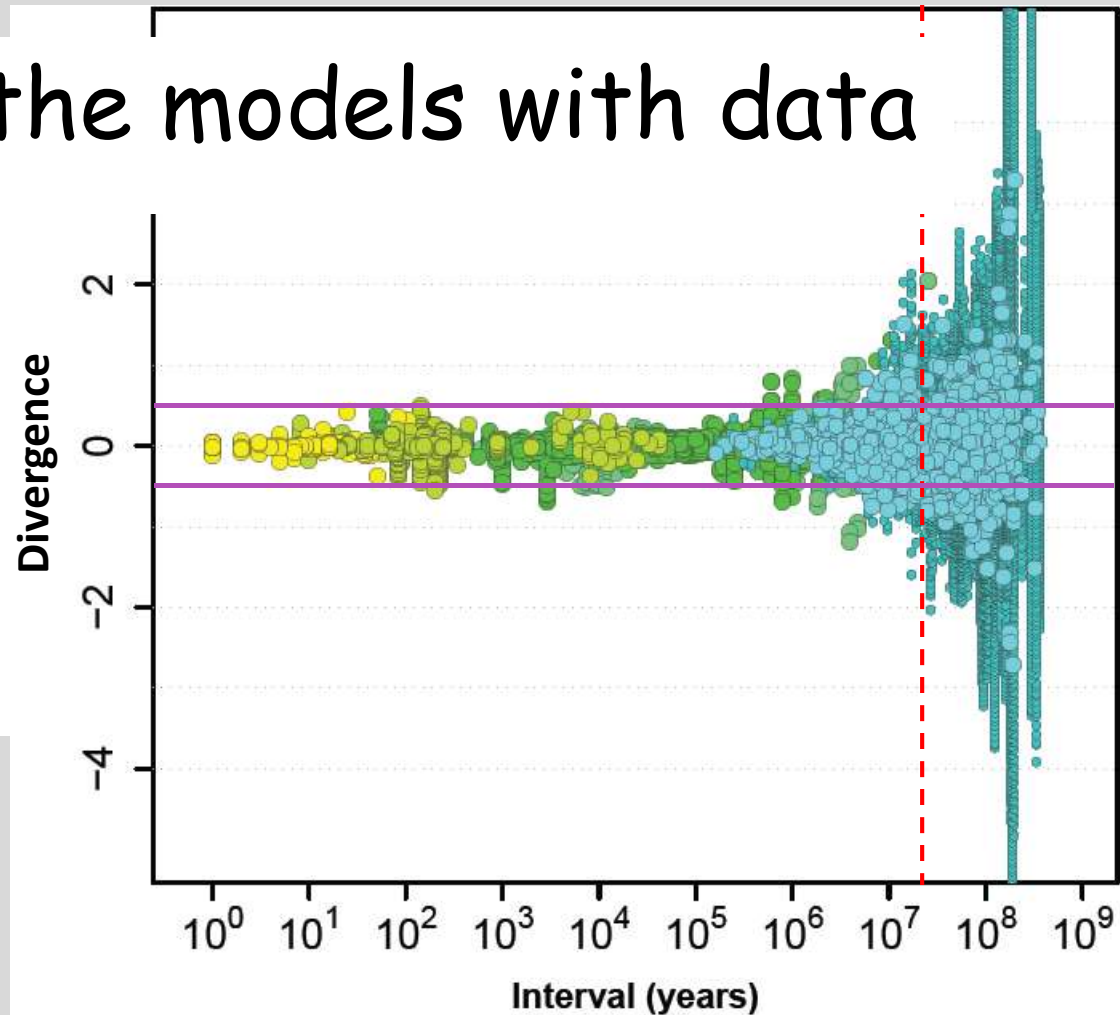
5. Challenging the models with data

White noise
distribution
(dashed)

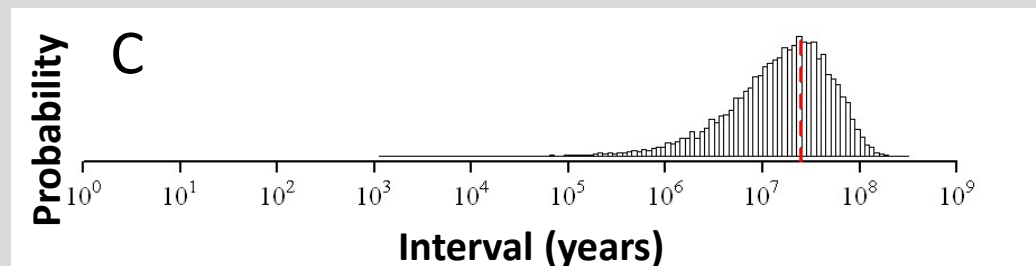
Burst size
distribution
(solid)



Probability



Burst timing distribution
(mean time between
bursts = 25 my)



What have we learned?

1. Quantitative genetic models can be used to model adaptive radiations.
2. Models in which an adaptive peak is stationary can not account for the scope of actual adaptive radiations.
3. Bounded evolution is a prevalent mode of evolution on all timescales.
4. Sudden departures from bounded evolution are rare but may account for the invasion of new adaptive zones.

References 1

- Lush, J. L. 1939. Animal Breeding Plans. Iowa State University Press.
- Lande, R. and S. J. Arnold 1983. The measurement of selection on correlated characters. *Evolution* 37: 1210-1226.
- Robertson, A. 1966. A mathematical model of the culling process in dairy cattle. *Animal Production* 8: 93-108.
- Grant, P. R. 1986. *Ecology and Evolution of Darwin's Finches*. Princeton Univ. Press.
- Endler, J. 1986. *Selection in the Wild*. Princeton Univ. Press.
- Price, T., P. R. Grant, H. L. Gibbs, and P. T. Boag. 1984. Recurrent patterns of natural selection in a population of Darwin's finches. *Nature* 309: 787-789.
- Kingsolver, J. G. et al. 2001. The strength of phenotypic selection in natural populations. *American Naturalist* 157: 245-261.

References 2

- Lande, R. and S. J. Arnold 1983. The measurement of selection on correlated characters. *Evolution* 37: 1210-1226.
- Lande, R. 1979. Quantitative genetic analysis of multivariate evolution, applied to brain: body size allometry. *Evolution* 33: 402-416.
- Schluter, D. 1988. Estimating the form of natural selection on a quantitative trait. *Evolution* 42: 849-861.
- Phillips, P. C. & S. J. Arnold. 1989. Visualizing multivariate selection. *Evolution* 43: 1209-1222.
- Blows, M. W. & R. Brooks. 2003. Measuring nonlinear selection. *American Naturalist* 162: 815-820.
- Estes, E. & S. J. Arnold. 2007. Resolving the paradox of stasis: models with stabilizing selection explain evolutionary divergence on all timescales. *American Naturalist* 169: 227-244.
- Schluter, D. & D. Nychka. 1994. Exploring fitness surfaces. *American Naturalist* 143: 597-616.
- Brodie, E. D. III. 1992. Correlational selection for color pattern and antipredator behavior in the garter snake *Thamnophis ordinoides*. *Evolution* 46: 1284-1298.
- Arnold, S.J. 1988. Quantitative genetics and selection in natural populations: microevolution of vertebral numbers in the garter snake *Thamnophis elegans*. Pp. 619-636 *IN*: B.S. Weir, E.J. Eisen, M.M. Goodman, and G. Namkoong (eds.), *Proceedings of the Second International Conference on Quantitative Genetics*. Sinauer, Sunderland, MA
- Arnold, S.J. and A.F. Bennett. 1988. Behavioural variation in natural populations. V. Morphological correlates of locomotion in the garter snake *Thamnophis radix*. *Biological Journal of the Linnean Society* 34: 175-190.
- Kingsolver, J. G. et al. 2001. The strength of phenotypic selection in natural populations. *American Naturalist* 157: 245-261.

References 3

- Lande, R. 1976. Natural selection and random genetic drift in phenotypic evolution. *Evolution* 30:314-334.
- Lande, R. 1979. Quantitative genetic analysis of multivariate evolution, applied to brain: body size allometry. *Evolution* 33: 402-416.
- Lande, R. 1980. Sexual dimorphism, sexual selection, and adaptation in polygenic characters. *Evolution* 34: 292-305.
- Hansen, T. F., and E. P. Martins. 1996. Translating between microevolutionary process and macroevolutionary patterns: the correlation structure of interspecific data. *Evolution* 50: 1404-1417.
- Hansen, T. F., J. Pienaar, and S. H. Orzack. 2008. A comparative method for studying adaptation to a randomly evolving environment. *Evolution* 62:1965-1977.
- Estes, E. & S. J. Arnold. 2007. Resolving the paradox of stasis: models with stabilizing selection explain evolutionary divergence on all timescales. *American Naturalist* 169: 227-244.
- Uyeda, J. C., T. F. Hansen, S. J. Arnold, and J. Pienaar. 2011. The million-year wait for macroevolutionary bursts. *Proceedings of the National Academy of Sciences U.S.A.* 108:15908-15913.
- Arnold, S. J. 2014. Phenotypic evolution, the ongoing synthesis. *American Naturalist* 183: 729-746.