Measuring natural selection on the transcriptome

John R. Stinchcombe[1,2] and John K. Kelly[3]

1. Department of Ecology and Evolutionary Biology, University of Toronto, Toronto, ON, Canada
2. Koffler Scientific Reserve at Joker's Hill, University of Toronto, King, ON
3. Department of Ecology and Evolutionary Biology, University of Kansas, Lawrence, Kansas, United States of America

Emails: john.stinchcombe@utoronto.ca
jkk@ku.edu

ORCIDs: https://orcid.org/0000-0003-3349-2964
https://orcid.org/0000-0001-9480-1252

Summary

The level and pattern of gene expression is increasingly recognized as a principal determinant of plant phenotypes and thus of fitness. The estimation of natural selection on the transcriptome is an emerging research discipline. We here review recent progress and consider the challenges posed by the high dimensionality of the transcriptome for the multiple regression methods routinely used to characterize selection in field experiments. We consider several different methods, including classical multivariate statistical approaches, regularized regression, latent factor models, and machine learning, that address the fact that the number of traits potentially affecting fitness (each expressed gene) can greatly exceed the number of plants that researchers can reasonably monitor in a field study. While such studies are currently few in number, extant data is sufficient to illustrate several of these approaches. With additional methodological development coupled with applications to a broader range of species, we believe prospects are favorable for directly characterizing selection on gene expression within natural plant populations.

Introduction

One of the fundamental goals of evolutionary biology is to understand how natural selection acts on phenotypes. Understanding the form, strength, and direction of selection is crucial to making predictions about the evolutionary trajectory of traits, understanding adaptation, and quantitatively testing alternative hypotheses about the extent to which organismal features evolve by adaptive or non-adaptive mechanisms. For this reason, evolutionary biologists have devoted considerable effort to measuring natural selection in field, experimental, and common garden environments (Kingsolver et al. 2001, 2012; Siepielski et al. 2013). While the rapid progress in molecular biology and genomics continually offers the promise of characterizing the genetic basis of complex traits (Hill 2010), there is a growing realization that these techniques and approaches yield a suite of molecular phenotypes that are themselves amenable to evolutionary (and genetic) analysis. Here we outline the prospects and challenges for characterizing natural selection on one particularly relevant– and increasingly attainable– set of molecular phenotypes, gene expression.

Several lines of evidence suggest that gene expression is an important determinant of organismal fitness, and thus likely to experience selection. Early experimental results, from mutation accumulation experiments in which the strength of selection has been minimized or reduced, suggested that stabilizing selection was acting on gene expression (Rifkin et al. 2005, Gilad et al. 2006). Likewise, observations from the microarray-era indicated that populations experiencing different environmental conditions can diverge in gene expression, even in the face of substantial gene flow (Oleksiak et al. 2002), potentially indicating the past action of selection. More recent studies have demonstrated changes in gene expression in response to severe weather events like cold snaps (Campbell-Staton et al. 2017), between ancestors and surviving descendants of droughts (Hamann et al. 2021), and in response 3-4 generations of experimental evolution in the field under new ecological conditions (Ghalambor et al. 2015). Collectively, these and other studies reveal that gene expression can and does evolve on a wide array of time-scales, including in the laboratory (Rifkin et al. 2005), between adjacent populations of the same species (Oleksiak et al. 2002), in response to severe weather events (Campbell-Staton et al. 2017; Hamann et al. 2021), and in ecologically realistic, complex communities within a handful of generations (Ghalambor et al. 2015, 2018).

Despite prominent examples of gene expression evolution on microevolutionary timescales, as well as theorizing on its relevance on macroevolutionary time scales (e.g., King and Wilson 1975), we have few direct estimates of natural selection on gene expression. In contemporary populations, is gene expression subject to stabilizing selection as first predicted, or is it frequently subject to directional selection as might be

deduced from these studies of evolutionary divergence on short time scales? How does the strength of selection on gene expression compare to that on 'macroscopic' traits such as life history, morphology, or behavior? Are the levels of transcription among multiple genes in the transcriptome sufficiently correlated as to require distinguishing between direct and indirect selection? Is there a relationship between the level of expression and the strength of phenotypic selection, analogous to the relationship between the level of expression and rates of molecular evolution (Wright et al. 2004, Slotte et al. 2011)? These and a host of other questions require extending the Lande-Arnold revolution (Lande and Arnold 1983; Svensson 2023) from traditional macroscopic phenotypes to include gene expression.

Transcriptomes as Quantitative Traits

Progress on these questions starts with the recognition that gene expression is itself a quantitative trait. The expression levels of genes across the genome are quantitative traits with strong environmental influences combined with multi-locus genetic effects (Liu et al. 2019). In fact, given that modern RNA-seq experiments often obtain expression estimates for many genes simultaneously (N in the 1,000s), the transcriptome is really a collection of vectors (or a matrix), as expression levels of a gene change with tissue, lifestage, and the expression of other genes. Considering the transcriptome as a set of correlated characters with a quantitative genetic perspective offers several insights. First, the transcriptome is hugely multivariate and thus offers investigators a chance to measure a large number of phenotypes simultaneously. In addition, by characterizing the phenotype in the broad sense, the traits measured are less prone to bias about the types of traits that might be important or under strong selection (e.g., size versus floral traits, those involved in mating versus anti-herbivore defense), although important choices must still be made about the time and tissue sampled. Perhaps most importantly, there is a well-developed machinery to analyze selection on correlated quantitative traits (Lande & Arnold, 1983; Rausher, 1992). However, the application of quantitative genetics to the transcriptome must confront the serious challenge of scale.

Most studies of phenotypic selection utilize a regression framework. In the simplest implementation of this approach, an estimate of relative fitness (e.g., individual seed set divided by mean seed set for the population) is regressed on a single phenotype in a univariate regression. In the context of gene expression, this would involve regressing an estimate of relative fitness on the expression of an individual gene, for all the individuals in the experimental population or sample. If expression has been standardized (i.e., $\bar{x} = 0$ and $\sigma = 1$), the resulting parameter estimate is the standardized selection differential for the expression of that gene; positive values would indicate that

greater expression of the gene was associated with increased relative fitness. Groen et al. (2020) applied this approach to populations of rice growing under field and drought environments. They found that selection differentials for gene expression were generally weak, but stronger under drought than well-watered conditions.

The scale of the transcriptome introduces two key problems with the univariate approach. First, RNA-seq experiments estimate the expression of thousands of genes at a time. Simply repeating a univariate analysis for all the genes for which one has data introduces severe multiple testing problems: A large number of genes associated with relative fitness will undoubtedly be false positives. Addressing the number of tests thus requires multiple testing or false discovery rate corrections. Second, selection differentials measure total selection on a phenotype, which is the sum of direct selection on the trait and indirect selection through correlated traits (Lande and Arnold 1983). Because the expression of any individual gene is likely to be correlated with the expression of other genes (and other traits), a selection differential alone cannot tell whether it is the expression of a focal gene that is directly important for relative fitness, or whether the expression of that gene is simply correlated with other traits that are under selection.

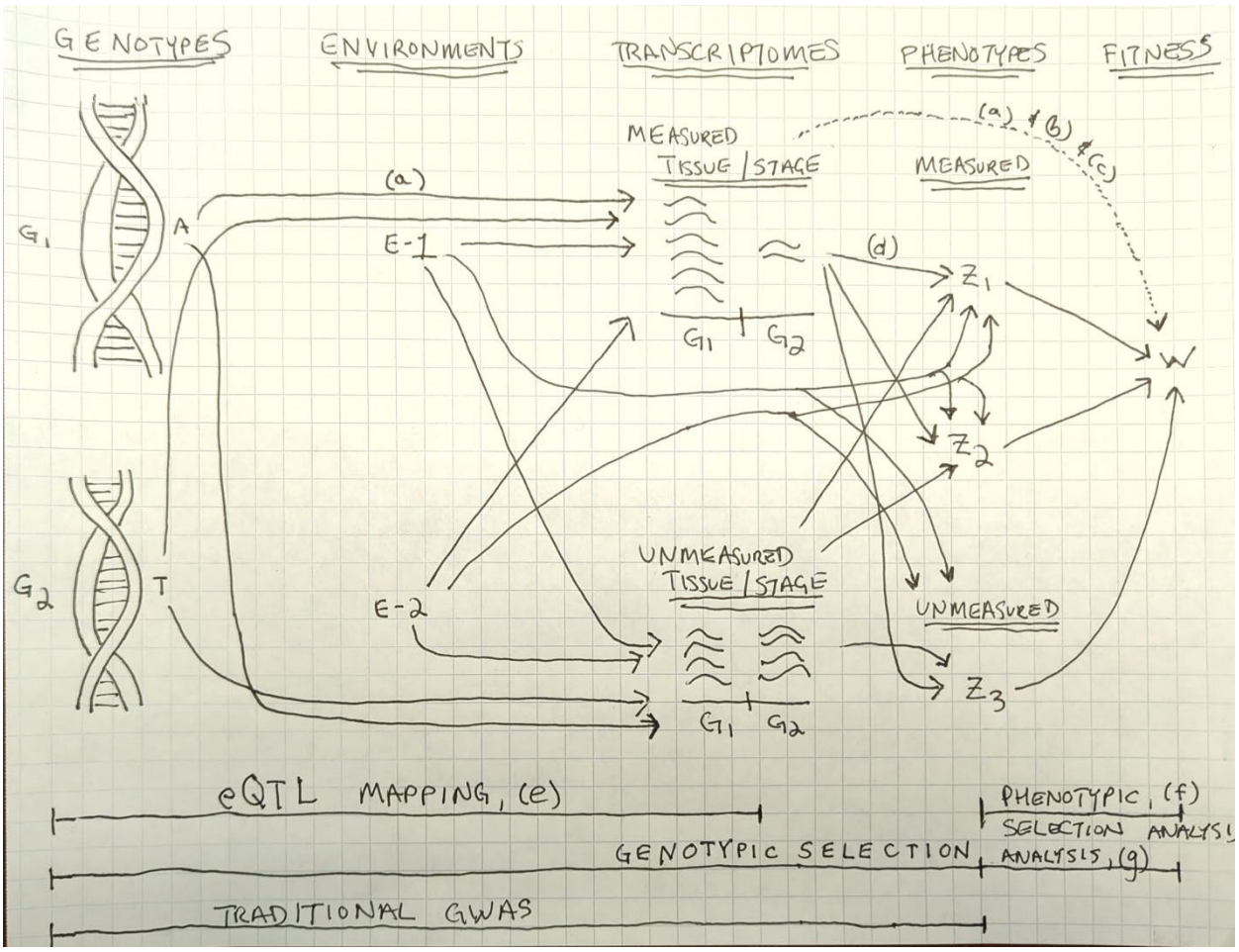

Figure 1. A schematic depicting the mapping from genotype to fitness. From left to right. We present a hypothetical case of two genotypes (G1 and G2) and two environments (E1 and E2) to illustrate how genetic variation and environmental variation affect transcriptomes, phenotypes, and fitness. In the middle column, we highlight that genetic and environmental variation may lead to differences in expression in some tissues and stages (measured tissue/stage) but not others (in this case, an unmeasured tissue/stage). Expression and environmental variation, in turn, both affect macroscopic phenotypes (z1, z2, z3). In this case, we highlight that while z1 and z2 have been measured, it is likely that unmeasured phenotypes (z3) are affected by expression and also affect fitness. In the arrows leading to fitness, we note that expression can affect fitness directly (dotted arrow) and via phenotypes (z1 and z2). Bars across the bottom are labeled with common analytical approaches to understanding expression, the genetic basis of traits, and selection. Key paths: (a) Groen et al. (2020), (b) Stinchcombe and Henry (2025), (c) Figure 2, this paper, (d) Brown and Kelly (2022), (e) Josephs et al. (2015, 2020), (f) Lande and Arnold (1983), (g) Rausher (1992).

The standard approach for measuring selection on (potentially) correlated traits involves multiple regression (Lande and Arnold 1983; Figure 1 path (f)). In this context, a regression of relative fitness on the expression of all the genes in the transcriptome

would yield selection gradients for gene expression. These gradients measure the direct effect of expression on relative fitness, accounting for the effects of the other traits (i.e., expression of other genes) included in the model. While promising in the abstract, with real data and sample sizes, such a model quickly runs into the *N-p* problem: there are far more parameters to estimate (*p*) than there are total samples (*N*) in even the most heroic of experiments. Consequently, one of the primary advantages of the Lande-Arnold (1983) approach–its ability to distinguish direct and indirect selection on correlated traits–is lost. In the remaining sections, we outline a handful of promising statistical and experimental approaches that can be used to address the *N - p* problem of measuring selection gradients for transcriptomes.

Selection Gradients for the Transcriptome: Statistical Approaches

There are several statistical approaches for measuring selection gradients for gene expression, and here we comment on some variants that appear to be emerging in the literature. Our expectation is that there will be continued work in this area, and that future developments are likely. At their core, these methods share one fundamental feature: dimensionality reduction, the compression of the data so as to estimate fewer parameters than the sample size. To use a hypothetical example, if an investigator has estimates of fitness for 500 individuals, and estimates of expression for >500 genes in those same 500 individuals, the goal of these approaches is to reduce the problem to estimating selection from far fewer than 500 parameters (so that *N* is greater than *p*).

PCA and Gene Coexpression Modules

The most straightforward approach is likely familiar to many users of selection gradient analysis– principal component analysis (PCA). Because PCA is a widely used technique and familiar to many biologists, we do not consider the mathematical or technical details of its implementation; Jolliffe (2002) provides an extensive coverage. In short, after a PCA, an investigator obtains independent axes capturing variation in the original traits. In many cases, far fewer axes (PCs) are required to describe the data than there were original traits. In the context of gene expression, these PC axes can be used as independent variables to predict relative fitness. An important point is that fewer– ideally far fewer– PC axes have to be used than there were original traits, otherwise nothing is gained. Groen et al. (2020; Figure 1, path (a)) used this approach with PC axes, and were able to detect significant selection on several PC axes. They used these findings to detect selection on the expression of genes related to photosynthesis and growth.

One downside of this approach is that a PC axis reflects– simultaneously– all the individual traits included in the study. A PC score is a weighted average of the expression of all measured genes with the magnitude and direction of the weights differing among principal components. This can make PC scores difficult to interpret. Chong et al. (2018) illustrate a method to 'back-transform' selection estimates for PC scores into selection estimates on the original traits. They argued these are much easier to interpret and suggested the technique would be useful for studies of selection on gene expression, metabolomics, and other high dimensional traits. In brief, one performs some matrix algebra computations involving selection estimates for PC scores and the eigenvectors of the original PCA. This rotation yields an estimate of a selection gradient on individual gene expression traits, accounting for the patterns of correlation among the traits, but only within the portion of multivariate space described by the PC axes included (Chong et al. 2018). Similar calculations can be performed to estimate standard errors for these reconstituted estimates of selection gradients for gene expression.

Henry and Stinchcombe (2025, Figure 1, path (b)) also used PCA to understand selection on gene expression. Like Groen et al. (2020), they regressed relative fitness on PC axes of gene expression. However, rather than using the PC axes as objects of study in themselves, they used the methods described by Chong et al. (2018) to back-transform selection on PC scores into selection gradient estimates for individual genes. In their study of *Ipomoea hederacea* (Ivyleaf morning glory), they had estimates of relative fitness for 96 individuals, and estimates of gene expression for 2,753 genes throughout the genome. The best model used 61 PCs to describe patterns of variation in gene expression, which collectively explained 55% of variation in relative fitness. Turning these back into selection gradients for the expression of individual genes suggest several important, if tentative, findings about selection on gene expression. First, they found a very strong positive relationship between selection differentials and selection gradients for gene expression, suggesting that overall in their study much of the selection on gene expression was direct, rather than indirect due to the expression of other genes. Second, they found a wide distribution of selection gradients for expression, approximately symmetrical around zero: some genes were under selection for increased expression, and a similar number for decreased expression. Finally, they observed that selection gradients for gene expression were substantially smaller than their past findings of selection on size and life history traits in the same population (Henry and Stinchcombe 2023).

An alternative approach to dimensionality reduction is to first identify gene co-expression modules using programs like WGCNA (Langfelder and Horvath 2008). These modules are constructed by identifying sets of genes whose expression is more

tightly correlated with other genes in the module than genes in other modules. The expression of the genes within a module can be summarized with PCA– so-called eigen-genes– and the PC1 score for the first eigenvector of a module can be estimated for each individual in a data set. These PC scores represent a weighted sum of gene expression of the genes within the module. As before, PC scores for a module's expression– which might summarize the expression of dozens to hundreds of genes– can be used as 'traits' in Lande-Arnold style analyses.

Several investigators have applied this approach, relating gene coexpression module PC scores to aspects of plant performance, size, or life history traits that are likely to be under strong selection (e.g., Palakurty et al. 2018, Josephs et al. 2020, Brown and Kelly 2022). For example, Brown and Kelly (2022; Figure 1 path (d)) found that PC1 scores from twenty gene coexpression modules could explain 47% of variation in flower size in *Mimulus guttatus.* They used permutation testing to verify that these modules indeed significantly predicted flower size, and that the observed co-expression modules performed significantly better than random groupings of genes of the same size. In other words, the coexpression modules contain biological signal in predicting traits (in this case, flower size) beyond a random grouping of genes in the transcriptome. Flower size is not itself a fitness component, but is under strong selection in *Mimulus guttatus* (Mojica and Kelly 2010), suggesting that transcriptomic variation affecting flower size can also potentially affect fitness. Interestingly, while several studies have related eigen-gene expression from coexpression modules to performance and fitness traits, to our knowledge none have used the PC rotations of Chong et al. (2018) to estimate selection gradients for expression of the individual genes within the module.

The use of gene co-expression modules entails a few benefits and drawbacks that are worth considering. Co-expression modules have the benefit that individual genes appear in one and only one module. As a consequence, the interpretation of the expression of the entire module is more straightforward than the output of a PCA, where the expression of each gene will load onto all the PC axes. Discrete, non-overlapping modules, in our view, might offer greater biological interpretation of the types of genes (or GO categories) that are associated with any given module. One drawback of coexpression modules, or PC scores summarizing the expression levels of genes within a module (eigen-gene expression), is that the scores summarizing multiple modules are not guaranteed to be uncorrelated across a sample, in contrast to a PCA using all of the data. As a consequence, understanding selection on multiple modules simultaneously requires a multiple regression and the estimation of selection gradients.

Machine Learning

There is great enthusiasm for machine learning approaches in evolutionary biology (Schrider and Kern 2018). While this field is moving quickly and a full review is beyond our scope here (see Schrider and Kern 2018 for an entry point), there are several features of these algorithms that suggest promise in the context of measuring selection on gene expression. Machine learning approaches often focus on overall prediction rather than individual parameter estimation. In this context, it would be to predict relative fitness from expression of the set of genes for which investigators have expression, rather than hypothesis testing about the individual contribution of any one gene's expression. Several features of the mechanics of how the algorithms work aid this. First, data are often split into "training" and "testing" sets, which can prevent overfitting and noise being fit to the model, and allow an evaluation of the overall performance of the model. Second, many of the approaches identify features (gene expression in this case) in a way that reduces the overall number of parameters that are estimated, which is a start towards addressing the issue of the scale of the transcriptome. Third, in many cases the output of a machine learning algorithm is a measure of importance, rather than a parameter estimate like a selection differential or gradient– for example, the expression of these genes are important in determining whether an individual survives or dies before reproduction.

Assuming that as an evolutionary biologist one has managed to implement one of the many machine learning algorithms available, and obtained a list of genes (features) whose expression is related to a fitness component, how does one make that information compatible and conversant with traditional measures of selection like differentials or gradients? One potential way forward is to use this reduced set of genes– that having survived cross-validation, evaluation in the testing data set, and acceptable performance metrics– appear to have expression that predicts relative fitness to estimate selection differentials and gradients the traditional way. In other words, one can use machine learning algorithms to identify an important subset of genes to focus on, and then traditional selection analysis to estimate selection differentials and gradients.

In Henry and Stinchcombe's (2025) study, they used machine learning classification algorithms to determine which genes' expression were important for determining whether an individual set seed versus failed to set seed. After model fitting, they identified 278 genes whose expression was identified as important for determining whether an individual set seed or failed to set seed; 29 of these genes were also identified with PCA, having strong selection gradients for their expression. Interestingly, the distribution of selection differentials and gradients for the expression of these 29 genes was bimodal, with few instances of weak (near-zero) selection. In other words, the machine learning classifier identified genes whose expression was important for

successfully setting seed and these genes showed the strongest patterns of phenotypic selection.

Regularized regression

Many evolutionary biologists (including ourselves!) find aspects of machine learning to be a bit of a black box: its hard to fully visualize the functions and models being fit by the algorithms. This is especially in the case of neural networks where the output of one function is used as the input for another, in a series of layers. Fortunately, there's a set of statistical techniques closely related to machine learning– and indeed used by some machine learning algorithms– that is closer to the typical statistical toolkits of practicing evolutionary biologists While to our knowledge regularized regression has not been used to estimate selection on gene expression, several features suggest that it could be useful.

Regularized regression is a useful analytical tool for fitting regressions with many predictors, varying degrees of multicollinearity between the predictors, and limited data (Morrisey 2014; Sztepanacz and Houle 2024). In contrast to ordinary least squares (OLS) univariate or multivariate regressions which estimate parameters by minimizing the sum of squared errors, regularized regressions minimize functions which include a penalty (Morrisey 2014; Sztepanacz and Houle 2024). A consequence of this is that individual parameter estimates are shrunk towards zero (i.e., regularized), which also reduces their variance. Parameter estimates obtained from regularized regression are thus biased compared to least-squares estimates, but the overall model predictive accuracy can be improved, in the presence of a bias-variance trade-off. For these reasons, regularized regression approaches are likely to be of use in the case of multicollinearity (Chong et al. 2018; Sztepanacz and Houle 2024).

Sztepanacz and Houle (2024) performed a simulation study that illustrates the potential utility of regularized regression for measuring selection on multiple, potentially highly correlated traits. While their focus was not on gene expression, the lessons likely apply. They showed that in the face of limited data, and multicollinearity between predictors (as might be expected with the expression of thousands of genes as traits), regularized estimates provided more accurate estimates of the total strength of selection and the overall multivariate direction of selection. The frequentist implementation of regularized regression, however, does not yield traditional measures of uncertainty like standard errors and statistical significance for the individual predictors (Morrissey 2014; Sztepanacz and Houle 2024). While this is a potential limitation for future meta-analyses which require estimates of uncertainty for parameters, it is important to note that the importance of a gene's expression in predicting relative fitness can be judged from the

368 magnitude of the estimated parameters, especially because regularized regression
369 approaches require the predictor data to be scaled to $\bar{x} = 0$ and $\sigma = 1$. In this manner,
370 gene's whose expression leads to large estimated coefficients are worthy of further
371 investigation and follow up. To our knowledge, no one has used regularized regression
372 to estimate natural selection on gene expression and transcriptomes.
373
374 **Measuring Selection Gradients at the Genotypic scale**
375
376 In evolutionary quantitative genetics, it is common to distinguish phenotypic selection
377 from response to selection. The former is the relationship between the multivariate
378 phenotype and fitness while the latter is determined by the mapping from genotype to
379 phenotype and requires an additional generation to measure. Separating selection from
380 response enables an operational division of labor. Field studies without a genetic
381 component can characterize selection, usually employing the Lande-Arnold regression
382 framework. Given phenotypic selection estimates, an evolutionary response can be
383 predicted using estimates of additive genetic variances and covariances from genetic
384 experiments. Genetic statistics can be estimated from classical breeding designs or
385 pedigrees or from genomic genotyping of individuals (Lynch and Walsh 1998).
386
387 The separation of selection from response is certainly convenient, but it is encumbered
388 with serious assumptions (Morrissey et al. 2010). There are many situations in which it
389 is advantageous to predict fitness from genetic statistics. One downfall of predicting
390 fitness directly from phenotypic traits (of any variety) is the possibility that the
391 relationship may be environmentally induced (Mitchell-Olds and Shaw 1987; Price et al.
392 1988; Rausher 1992). For plant systems, it is easy to envision that individuals growing
393 in high resource soils (e.g., high N, P, or K) both have higher fitness and also larger
394 values of traits requiring N and P– for example, size, branching, or plant defense traits.
395 In this instance, a naive application of the Lande-Arnold approach would detect
396 selection on these traits even if size, branching, and plant defense have no effect on
397 fitness at all. In this scenario, both fitness and the other phenotypic traits are
398 responding, independently, to soil resource variation, and investigators observe an
399 environmentally induced relationship rather than a causal one. In regression terms, one
400 has omitted a 'trait' (in this case, soil NPK concentrations) that is correlated with both
401 the predictors and the response variable, leading to inaccurate parameter estimates.
402 Importantly, such relationships will not lead to responses to selection and evolutionary
403 change (Rausher 1992). It is highly likely that gene expression, as a trait, will be
404 environmentally sensitive to aspects of soils, temperature, weather, abiotic and biotic
405 conditions, and a multitude of other influences. *A priori*, this suggests that the potential
406 for environmental covariances to bias estimates of phenotypic selection on gene
407 expression is high.
408

Fortunately, Rausher (1992; Figure 1, path (g)) provided a solution to this problem: estimating selection using either breeding values or estimates of genotypic values for both phenotypes and fitness. While this approach comes at a cost of sample size and statistical power (Stinchcombe et al. 2002), covariances between fitness and phenotypes estimated with breeding values reflect genetic relationships, rather than environmentally induced ones. As a consequence, not only are parameter estimates of selection more accurate, but they also reflect relationships that have the potential to produce evolutionary change (Stinchcombe et al 2002). While formal studies remain rare (but see Stinchcombe et al. 2002 and Hadfield 2008), existing evidence suggests that many estimates of phenotypic selection on macroscopic traits are highly biased by environmental covariances (Stinchcombe et al. 2002; Kruuk 2002; Morrissey et al. 2012; Hajduk et al. 2020).

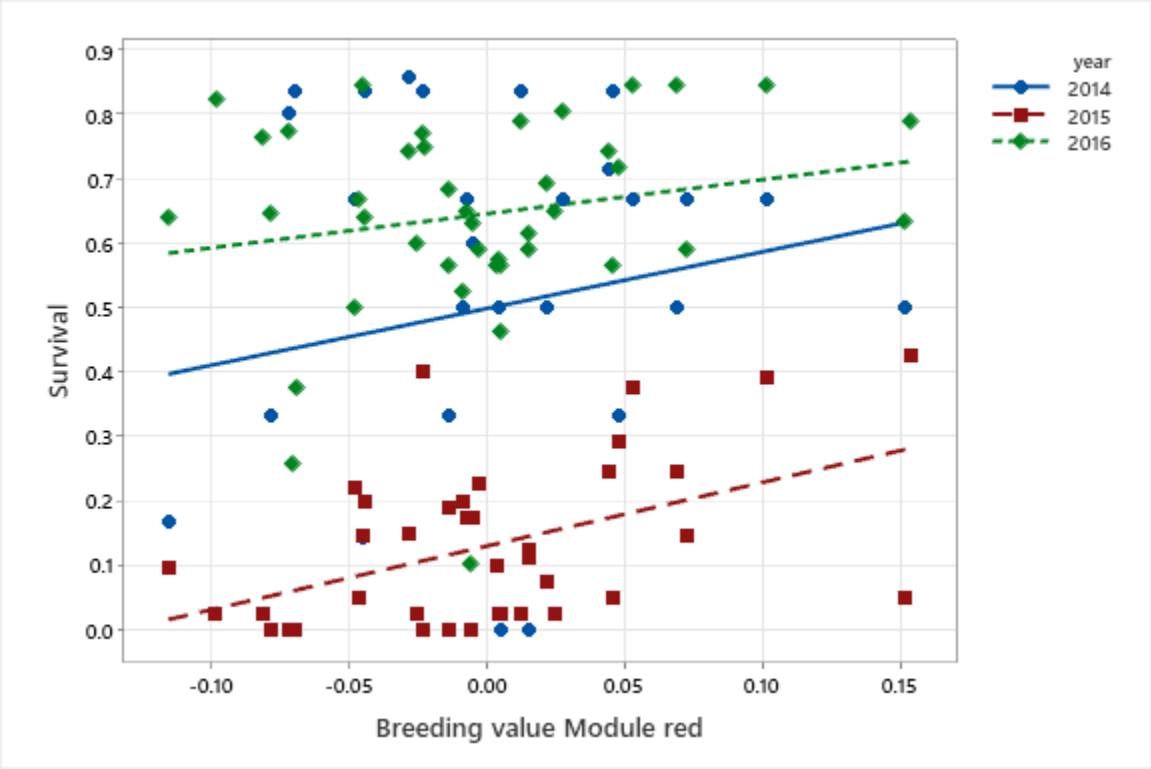

Figure 2. Selection gradients for expression module 'Red' are positive for survival in all three years. The overall effect of Red on survival to flower (all years included) is significantly positive ($F_{1,107} = 6.43$, $p = 0.013$), although only the 2015 regression, where survival was generally low, is significant when considered in isolation ($F_{1, 38} = 11.07$, $p < 0.002$).

The breeding value regression approach is as applicable to gene expression as it is to macro-phenotypes. This is also true for the compression methods discussed in the previous section (e.g. PCA and WGCNA). They can be applied as readily to breeding value regressions as to phenotypic regressions. To illustrate, we revisit the gene expression modules of Brown and Kelly (2022) which were obtained for homozygous

lines of *Mimulus*. Many of these same lines were intercrossed to make F_1 plants and then measured for survival and reproductive success in the natural habitat by Troth *et al.* (2018). The breeding values (a.k.a. additive genetic values) for the F_1 plants are the average of the values obtained from the parental lines – this is how breeding values work (Lynch and Walsh 1998). As a consequence, we can use gene expression estimates obtained in the greenhouse to predict fitness in nature. Over three successive generations, one expression module (Red) was a consistent predictor of survival to flower in each of the three field seasons (**Fig 2;** note that Fig. 2 is path (c) in Fig. 1). In the greenhouse, genotypes with high values for 'Red' are associated with earlier germination (Brown and Kelly 2022).

Unlike phenotypes, which are unique features of individual plants, breeding values are 'portable'; indeed, this is one of their features at the heart of their success in agricultural applications. They can be carried across experiments whenever genotypes can be replicated. Portability enables highly powered experiments because gene expression can be studied on large samples of plants grown under controlled conditions (e.g., the greenhouse environment). Also, because breeding values of expression are the predictors of field fitness, we avoid the serious difficulty of environmental factors inducing spurious correlations between phenotype and fitness. The downside is that expression levels in the greenhouse could prove to be the "wrong traits." The same genes could be expressed in different ways under field conditions than under those used to obtain breeding values, or different genes could be expressed in response to different environments. This would be an example of genotype by environment interaction, where the amount of expression, or which genes are expressed, depends on the environmental context (greenhouse or field). Of course, this is alway a concern with RNAseq studies, whether the transcripts sampled from a particular tissue at a particular life stage are the most relevant determinants of phenotype and/or fitness.

To date, there has been a great deal more work on the genetic basis of transcriptional variation than on how this variation affects fitness. Research on the genetics of gene expression has also been confronting the issue of scale. Above, we discussed PCA and WGCNA based on the 'P matrix', the variances and covariances among plants in the expression level of each gene (the phenotype). An alternative approach is to partition the phenotypic variance into genetic and environmental components and then apply the compression to these underlying components. For example, Blows et al (2015) show that the genetic component of variation in expression of 8750 genes of *Drosophila serrata* could be distilled into the contributions of a much smaller number of underlying variables using matrix completion methods.

A qualitatively different approach to understanding gene expression evolution is to apply factor analysis or latent factor modelling. While these approaches are more common in psychology and other disciplines, they have received less adoption in evolutionary biology (for exceptions, see McGuigan and Bows 2010; Frichot et al. 2013). In the context of gene expression, the idea is that the expression of each gene is influenced by a limited number of underlying 'factors.' These factors are not directly observed but can be modeled and estimated from data. Variation in factors can be partitioned into genetic and environmental components, and through the mapping from the factors to the expression levels of genes, one can characterize the variances and covariances for the entire transcriptome. The problem thus shifts from analyzing the genetic variances and covariances in the expression of thousands of individual genes to understanding the variances and covariances of a much more limited set of inferred factors. Two implementation methods– Bayesian Sparse Factor Analysis (BSFA; Runcie and Mukherjee 2013) and MegaLMM (Runcie et al. 2021)– have been developed that are suited to predicting the high dimensional structure of genetic variances and covariances of the transcriptome from a more limited set of variables. These approaches provide a natural means to reduce the dimensionality of the determination of gene expression levels from genetic and environmental influences. Correlations between expression levels emerge when different genes share a common factor.

Factor analysis could be applied to estimate selection on the transcriptome in either of two distinct ways. The first would be to apply BSFA or MegaLMM strictly to the partitioning of transcriptome variation into genetic and environmental components, without including fitness variables in the model. Given estimated breeding values for factors, one could predict field fitness in a way analogous to the *Mimulus* example of Fig 2 (except using factors instead of module eigenvalues). This approach addresses the scale issue because factors are uncorrelated with each other. Moreover, given the mapping from factors to expression levels, one can extrapolate from selection gradients on factors to gradients on individual genes. The second way would be to apply factor analysis to transcriptomes and fitness measurements simultaneously. This is essentially adding fitness measures to the list of phenotypes (transcript levels). One then estimates genetic and environmental covariances among the expression levels of genes simultaneously with their covariances with fitness. Estimated factors with strong contributions from fitness would be identified as under selection. Genes whose expression loaded heavily on those factors are thus under selection.

The simultaneous approach has the advantage that the sparse factor model directly estimates the genetic covariance between fitness and gene expression. This is the predicted change in the mean expression level into the next generation (Robertson 1966, Price 1970, 1972). The two-part method is more consistent with the traditional

quantitative genetic approach based on regression where we distinguish traits as independent variables (predictors) and fitness components as dependent variables. Oftentimes, the joint distribution for traits can be treated with a multivariate normal distribution. However, fitness components are usually non-normal (e.g. binary for survivorship, negative binomial for fecundity, etc). It may be easier to accommodate the differing distributions for transcript variation and fitness components in a regression framework. A second reason to separate fitness from characterization of transcriptome variation is that we often expect the relationship between trait values and fitness to be non-linear due to stabilizing, disruptive, or correlational selection.

Conclusions

Several common themes emerged from our overview of techniques for characterizing selection on the transcriptome even though many techniques are still in areas of active development. First, at their heart, most of the approaches we have discussed approach the *N*-*p* problem through some form of compression and reduction in the number of parameters that have to be estimated. As long as the sample sizes for the number of genes for which expression is measured with sequencing technologies exceeds the number of individuals in experiments, some form of data reduction or compression will remain a requirement.

Second, we perceive distinct analysis paths which investigators can take, based on the data in hand and the tractability of the system. For species in which it is possible to perform breeding designs, create known and replicated genotypes, and/or generate inbred lines, analyses based on breeding values should be pursued. In these systems, expression can be measured in the greenhouse or growth chamber and fitness estimates obtained from the same genotypes (or relatives with predictable breeding values). In the case of inbred lines, successive estimates of transcriptomes, performance, and fitness could be obtained from immortalized genotypes that are exposed to a variety of growth conditions. In contrast, for species or systems where it is difficult to obtain immortalized genotypes– or where cost constraints preclude characterizing the transcriptomes of many genotypes– estimates of selection on the transcriptome are more akin to the field studies of selection on macro traits that followed the Lande and Arnold (1983) paper. The rich picture of how natural selection acts on morphological, behavioral, and life-history phenotypes is from a set of studies similar in design to a single-instance measurement of selection on the transcriptome (Henry and Stinchcombe 2025). We have drastically fewer estimates of selection on transcriptomes to characterize its strength, mode, and spatial or temporal consistency, perhaps because the approach and technology are in early development. More than 40 years ago, Arnold (1983) coined the expression “morphology, performance, fitness” in a

landmark paper describing how to understand variation in, and selection on, morphology. We suggest that an important area of research in the next 40 years of evolutionary biology will be to explore the mapping from gene expression to phenotype to fitness.

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