

Interpretable Ordinal Analysis for Complex Designs in Cell and Molecular Biology

MICalculato BLISS

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The Challenge

- Complex phenotypes are commonly ordinally measured by scoring.
- Rapid to Collect
- Difficult to Analyze
- **Testing Assumptions**
- Ordinal Regression
- Powerful
- Uncommon²

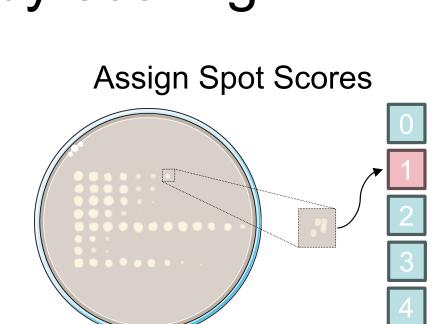


Figure 1. Example ordinal phenotype.

The Solution

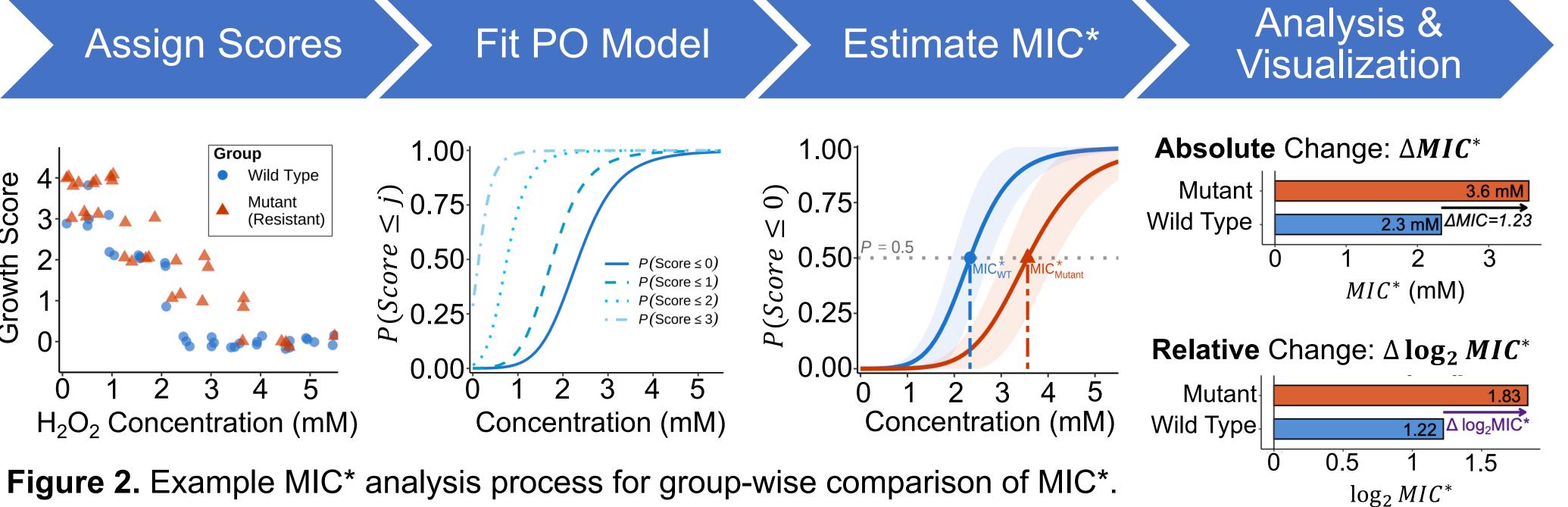
Convert ordinal scores into a quantitative, interpretable metric we call MIC*.

$$P(Y \le 0 | X, X_C = MIC^*) = 0.5$$

- Derived from ordinal regression model
- Biologically interpretable
- MIC = Minimum Inhibitory Concentration

The ordinalMIC Software Suite			
Tool	Purpose	Benefit	Access
BLISS Web App	Blinded Scoring Assess Consistency	Reduce Bias Browser Based	lewislabUARK.github.io/ BLISS
ordinalMIC R package	Perform Core Statistical Analysis	Powerful & Flexible	lewislabUARK.github.io/ordinalMIC
<i>MICalculator</i> Web App	Point-and-Click Tool for MIC* Analysis	Increased Accessibility	lewislabUARK.github.io/ MICalculator

Table 1: Resources available for ordinal scoring and *MIC** analysis.



Estimator Performance

MIC* is Powerful Estimator

Monte Carlo Simulations (N=10⁷) of factorial G×E design confirm framework's utility.

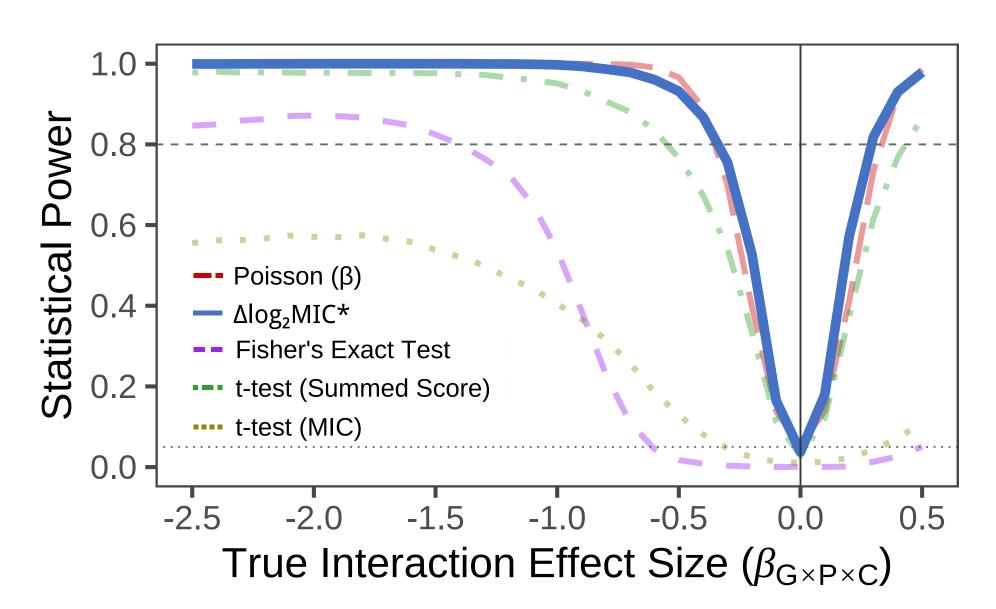


Figure 5: Power analysis for ΔMIC^* vs alternative analyses observed across a range of effect sizes.

- Sensitive: Achieves >80% power to detect 41% increase in expected count.
- Specific: Nominal Type I error rate (~5%)
- Accurate: Low bias with mean bias 0.0026 (IQR: -0.011 to 0.018) for MIC* estimates

Statistical Framework

Proportional Odds (PO) Model:

$$logit(P(Y_i \le j)) = \alpha_j - X_i \beta$$

The MIC* Metric:

$$MIC^* = g^{-1} \left(\frac{\alpha_0 - \sum \beta_k X_k}{\beta_C + \sum \beta_{Ck} X_k} \right)$$

Group Differences:

$$\Delta MIC^* = MIC^*_B - MIC^*_A$$

$$\Delta \log_2 MIC^* = \log_2 MIC^*_B - \log_2 MIC^*_A$$

Variance Estimation: $(g_A(\theta) = MIC^*_A)$

$$V(\Delta MIC^*) = (\nabla g_B - \nabla g_A)^T \sum (\nabla g_B - \nabla g_A)$$

Ex 1: Quantifying G×E

G×E = Genotype × Environment Interaction

Question: Does deletion of CTT1 abolish saltinduced peroxide resistance in yeast?

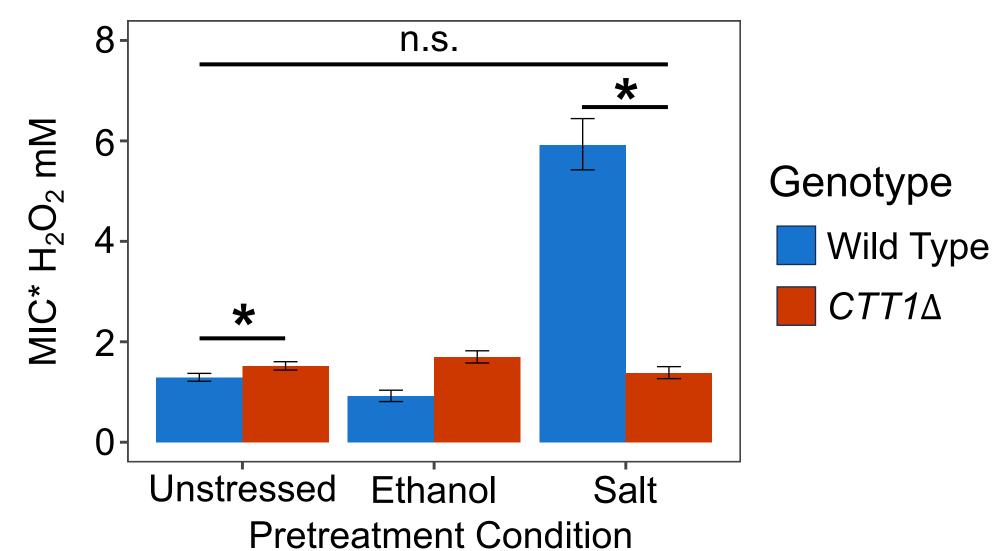


Figure 3. *MIC** for H₂O₂ resistance of Wild Type and CTT1\Delta mutants following salt pretreatment.3 Error bars represent 95% CI, * denotes p < 0.05.

Finding: Yes. Resistance phenotype for salt is completely dependent on the gene CTT1. $\Delta MIC^* = 0.09$ (95% CI: -0.04 to 0.23 mM H₂O₂)

Ex 2: Trait Mapping

Question: Can spot assays quantify ethanolinduced peroxide resistance inheritance?

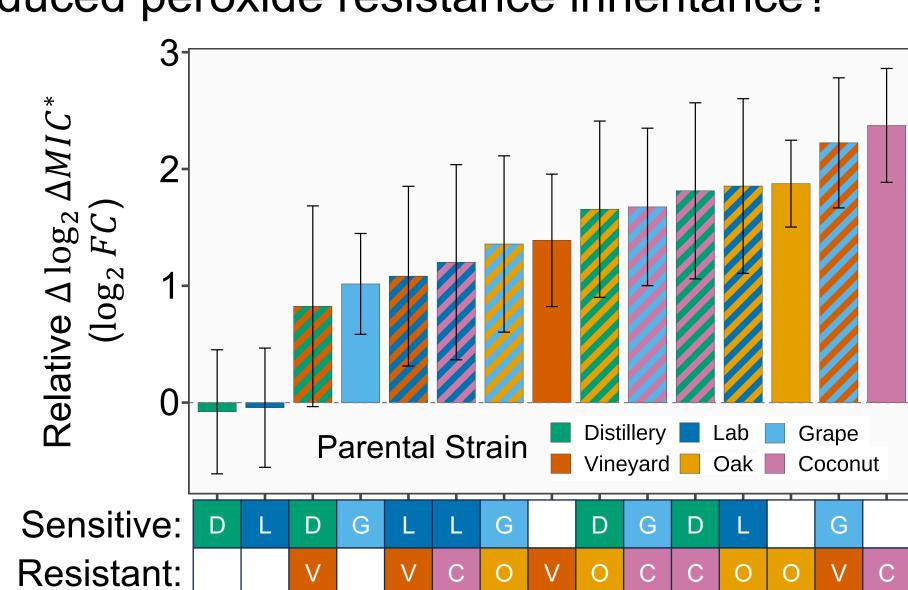


Figure 4. *MIC** for H₂O₂ resistance of wild yeast strains and crosses following ethanol pretreatment versus no pretreatment. Error bars represent 95% CI

Finding: MIC* reveals majority exhibit an intermediate phenotype, while the Grape × Vineyard cross exhibited enhanced resistance.

Take-Home Messages

- Stop Summing Scores. Conventional analyses of ordinal data are underpowered
- 2. Translate Scores to Biology. The MIC* framework converts ordinal scores into intuitive quantitative metric.
- 3. New Tools Available to Help. We provide complete, open-source workflow for research

References

[1] Agresti, A., 2010. Analysis of ordinal categorical data. John Wiley & Sons.

[2] Agresti, A. and Tarantola, C., 2018. Simple ways to interpret effects in modeling ordinal categorical data. Statistica Neerlandica, 72(3), pp.210-223.

[3] Scholes, A.N., Stuecker, T.N., Hood, S.E., Locke, C.J., Stacy, C.L., Zhang, Q. and Lewis, J.A., 2024. Natural variation in yeast reveals multiple paths for acquiring higher stress resistance. BMC biology, 22(1), p.149.

Acknowledgements

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