Identifying Selection in Experimental Evolution

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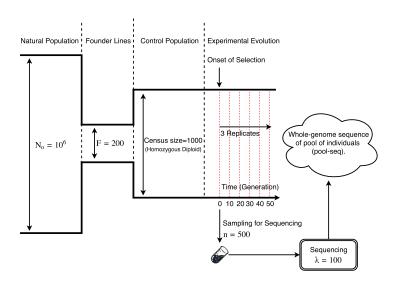
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An experiment design for *D. melanogaster*



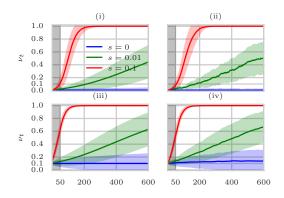
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Challenges (I)

 \bullet Small population size \Rightarrow strong drift

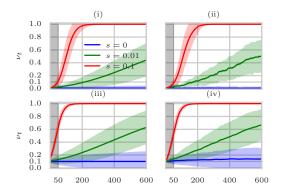
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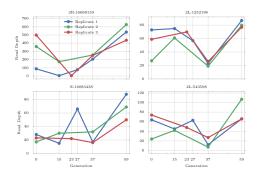


• Strong selection \Rightarrow Short fixation time \Rightarrow High LD \Rightarrow Difficult to locate favored allele

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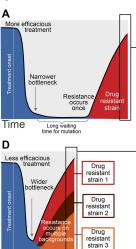
Challenges (II)

• Pool-seq data: Heterogeneous coverage for a variant

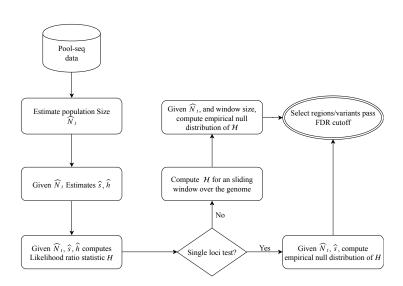


Challenges (III)

• Selection + Demography



CLEAR procedure



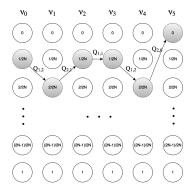
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Simplified Model (I)

• Suppose we have sequenced a whole (diploid, size=N) population every generation and exact allele frequency are given.

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- Wright-Fisher Markov chain, computes likelihood of a trajectory for a given N (a $2N \times 2N$ transition matrix Q)



 $P(\nu_0\,,\,\ldots\,,\nu_5) = \,Q_{1,2}\,\,Q_{2,1}\,\,Q_{1,1}Q_{1,2}\,Q_{2,0}$

Likelihood ratio test

- find \hat{N} and \hat{s} that maximizes likelihood of data.
- compute likelihood ratio, H statistic for each SNP:

 $H = \frac{\text{likelihood of data as if being under selection with } \hat{s}, \hat{N}}{\text{likelihood of data as if being neutral with } \hat{N}}$

Model (complete)

• In reality, population is sequenced after some (τ) generations. solution: use Q^{τ} in computing likelihoods.

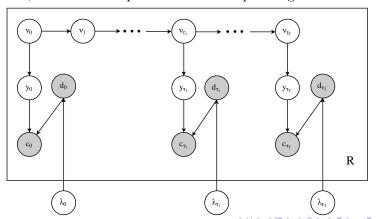


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Composite Likelihood for a Region

- Computing joint likelihoods of SNPs is infeasible (haplotypes are required) and intractable (requires estimating covariance).
- A heuristic is to compute composite (aka, pseudo) likelihood of the region L to reduce false-positives

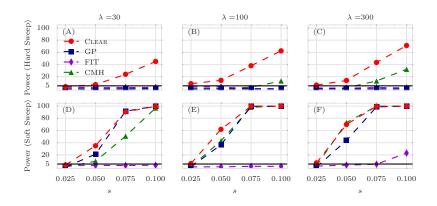
$$\mathcal{H} = \frac{1}{|L|} \sum_{\ell \in L} H_{\ell}$$

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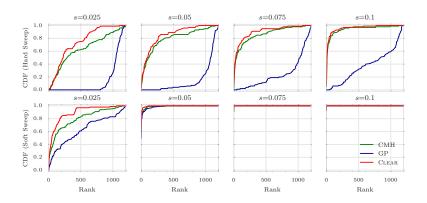
Performance in Detecting Regions under Selection

Each point represent power (TPR when $FPR \le 0.05$) of detection in 1000 simulations (500 neutral, 500 selection) of a 50Kbp window, for different coverages.



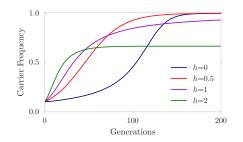
Localizing favored allele

Each curve depicts cumulative distribution of the rank of favored allele among (≈ 1150) variants, in 500 simulations.



Estimating parameters (I)

Our model estimates strength of selection s and overdominance h parameter for each variant.



- h = 0: recessive adaptive allele
- h = 0.5: directional selection
- h = 1: dominant adaptive allele
- h > 1 :overdominance

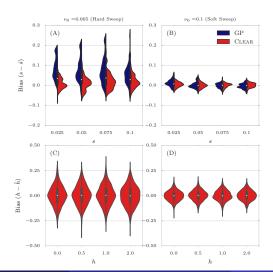
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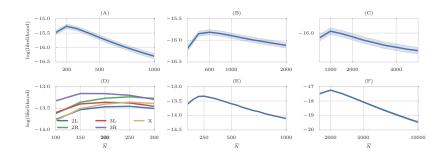
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Estimating parameters (II)

Distribution of bias of parameters in 500 simulations.



Estimating parameters (III)



Analysis of real data

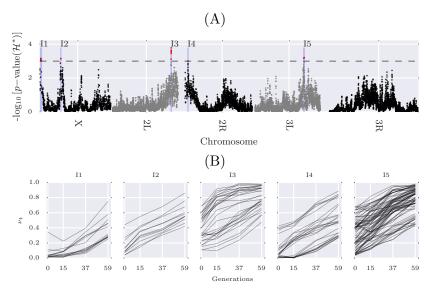
- A population of *D. melanogaster* is evolved for 59 generations, under alternative hot and cold temperatures.
- Coverage is different at generations and samples are not synchronized.
- Genome scan for sliding window size=50Kbp, steps=10Kbp
- $\hat{N} = 200$



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$D.\ melanogaster$



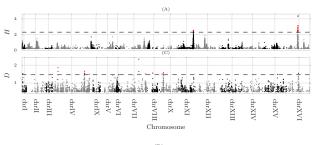
Outcrossing Yeast populations

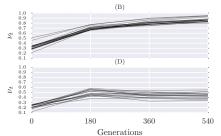
- 12 replicates of Yeast populations (census size $10^7 10^9$) are E&Red for 540 generations.
- $\hat{N} = 2000$
- two regions violating FDR cutoff are found.

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Outcrossing Yeast populations





Discussion

• An efficient method for analyzing full time-series read-count data is proposed.



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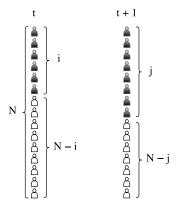
Discussion

- An efficient method for analyzing full time-series read-count data is proposed.
- By computing composite likelihood \mathcal{H} statistic is more robust to false positives.
- We can infer demographic changes as well as selection for and experiment.

Thanks!

Modeling genetic drift via Binomial sampling

• Drift: rate of sampling remain constant $\Pr(i \to j) = B(j; N, i/N)$

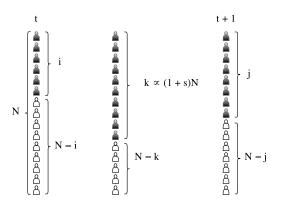


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Binomial Sampling with Selection

• In selection, we sample favored allele proportional to 1+s, and the alternate allele with weight 1. $\Pr(i \to j) = B(j; N, k/N)$



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