Identifying Selection in Experimental Evolution

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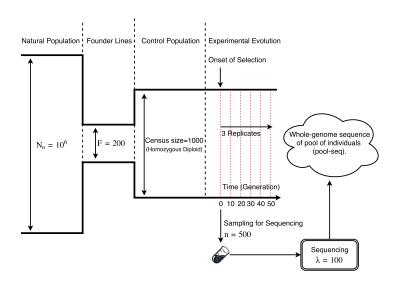
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March, 2017

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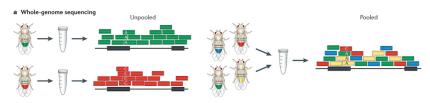
An experiment design for *D. melanogaster*



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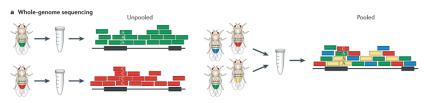
Whole-Genome Whole-Population Sequencing

• Pooled-Sequencing



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Nature Reviews Genetics 15, 749-763 (2014)

• Implication: only population allele frequency can be computed.

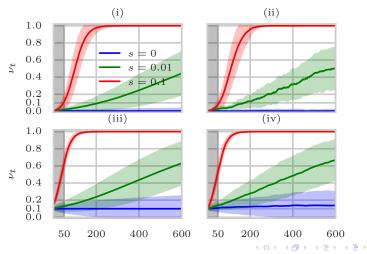
D. melanogaster vs Bacteria

- (i) Population size: $N_{Drosophila} \ll N_{Bacteria}$ Among other consequences: Mechanism of adaptation is standing variation in D. melanogaster while it is $de\ novo$ mutation in Bacteria.
- (ii) Reproduction: *D. melanogaster* has sexual reproduction (with crossovers) that helps localizing selection.
- (iii) In both cases we are interested in detecting partial sweeps.

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Dynamic of population allele frequency

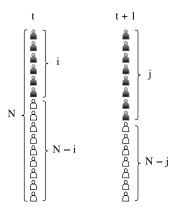
under different initial conditions and selection strengths frequency change differently



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Binomial Sampling

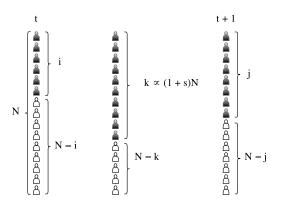
- In a finite population, we can model change in frequency of an allele via Binomial sampling.
- Drift: rate of sampling remain constant $\Pr(i \to j) = B(j; N, i/N)$





Binomial Sampling with Selection

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



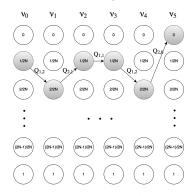
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Simplified Model (I)

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

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- A Markov chain, can compute likelihood of a trajectory for a given N and s (a $N \times N$ transition matrix Q)



 $P(v_0, \ldots, v_5) = Q_{1,2} \ Q_{2,1} \ Q_{1,1} Q_{1,2} \ Q_{2,0}$

Likelihood ratio test

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

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

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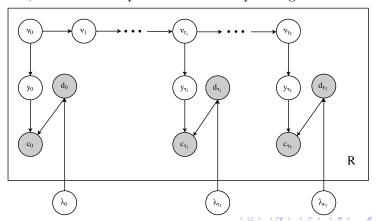
Model (complete)

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



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- Allele frequencies are unknown, and depth of each variant can be different, and finite sample is taken for sequencing.



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Composite Likelihood for a Region (I)

• So far we developed log-odds ratio statistics M (frequency data) and H (read count data) for each variant.

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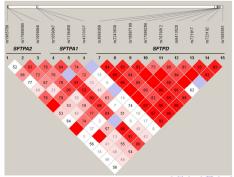
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- So far we developed log-odds ratio statistics M (frequency data) and H (read count data) for each variant.
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Composite Likelihood for a Region (I)

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- For a small region with L variants we can simply take the max score in the region, which is prone to false positives.
- We know that nearby variants can be correlated, esp. when selection is going on



Composite Likelihood for a Region (II)

• Computing joint likelihoods of SNPs is infeasible (haplotypes are required) and intractable (requires estimating covariance).



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Composite Likelihood for a Region (II)

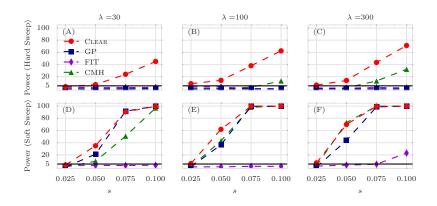
- Computing joint likelihoods of SNPs is infeasible (haplotypes are required) and intractable (requires estimating covariance).
- A heuristic is to compute composite (aka, pseudo) likelihood of the region L to reduce false-positives

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

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Performance in Detecting Regions under Selection

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



Detecting regions under selection: Observations

(i) Provides better and much robust performances to change of coverage.



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Detecting regions under selection: Observations

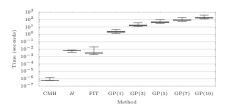
- (i) Provides better and much robust performances to change of coverage.
- (ii) It can detect well even when coverage is low, i.e., favored allele frequency (1/200 in hard sweep) is below accuracy of sequencing (1/30).

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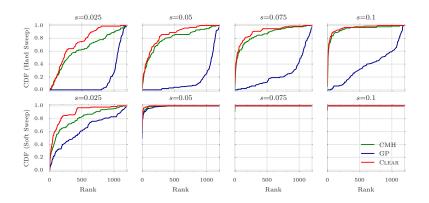
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- (i) Provides better and much robust performances to change of coverage.
- (ii) It can detect well even when coverage is low, i.e., favored allele frequency (1/200 in hard sweep) is below accuracy of sequencing (1/30).
- (iii) Run time is better or comparable with others.



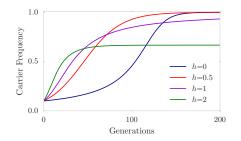
Localizing favored allele

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

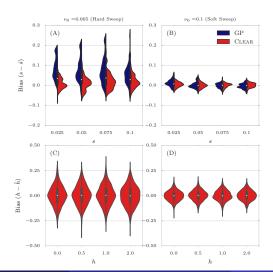
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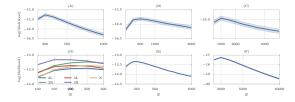
Estimating parameters (II)

Distribution of bias of parameters in 500 simulations.



Estimating parameters (III)

Assuming majority of the variants evolving neutrally, we can fit population size N on neutral model, i.e. Q(0,0,2N)



Hypothesis Testing

The statistical procedure involves:

- (i) Estimating population size, \hat{N} , over the whole genome.
- (ii) Estimating selection parameters for given \hat{N}
- (iii) Computing likelihood statistics.
- (iv) Hypothesis testing: The null distribution of likelihood ratio statistics are computed on a set of single locus drift simulations with population size of \widehat{N} . p-values and FDR is computed accordingly.

Analysis of real data

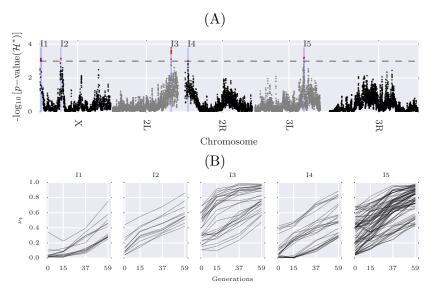
- A population of *D. melanogaster* is evolved for 59 generations, under alternative hot and cold temperatures.
- Coverage is different at generations and samples are not synchronized.
- Genome scan for sliding window size=50Kbp, steps=10Kbp
- $\hat{N} = 200$



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$D.\ melanogaster$



Outcrossing Yeast populations

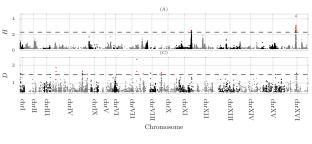
- 12 replicates of Yeast populations (census size $10^7 10^9$) are E&Red for 540 generations.
- $\hat{N} = 2000$
- two regions violating FDR cutoff are found.

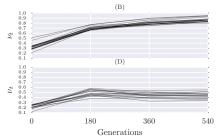
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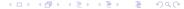
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Discussion

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- 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!