

Molecular Information Theory of Composite Sequence Motifs

Elia Mascolo¹, Ivan Erill^{1,2}

¹ University of Maryland Baltimore County, Baltimore, MD 21250, USA

² Universitat Autònoma de Barcelona, 08193 Bellaterra, Spain

Classical Theory for Sequence Motifs

Information as a decrease in *uncertainty* (entropy): $H_{\text{before}} - H_{\text{after}}$

$$R_{\text{frequency}} = \log_2(G) - \log_2(\gamma) = -\log_2\left(\frac{\gamma}{G}\right) \text{ (bits)}$$

number of positions in the genome number of target sites

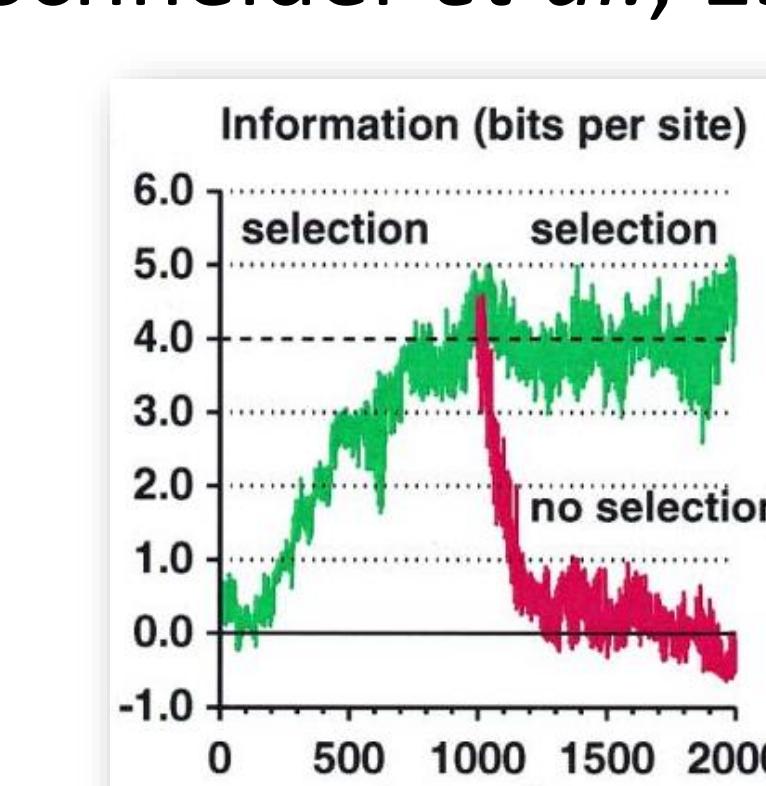
$\gamma = 3$

TF TF-binding site

$R_{\text{frequency}}$: information required to specify γ target sites on a genome of G bp.

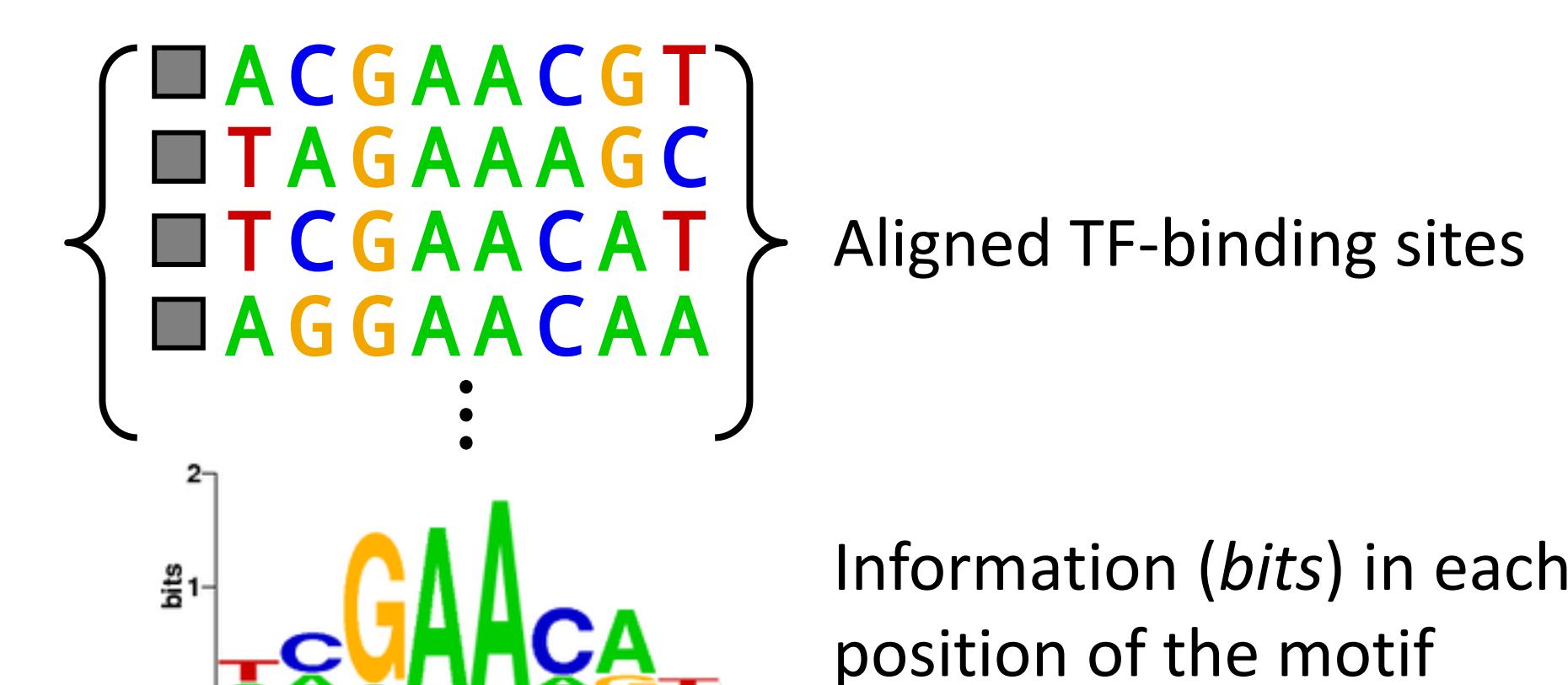
$$R_{\text{frequency}} \approx R_{\text{sequence}}$$

(Schneider et al., 1986)



(Schneider, 2000)

The information the transcription factor needs is encoded in the DNA sequence of its binding sites



R_{sequence} : information contained in the motif

Composite Motifs ($n = 2$)

$$R_{\text{frequency}} = \log_2(G^2) - \log_2(\gamma) = -\log_2\left(\frac{\gamma}{G^2}\right) \text{ (bits)}$$

number of dimer placements number of target placements

$\gamma = 3$

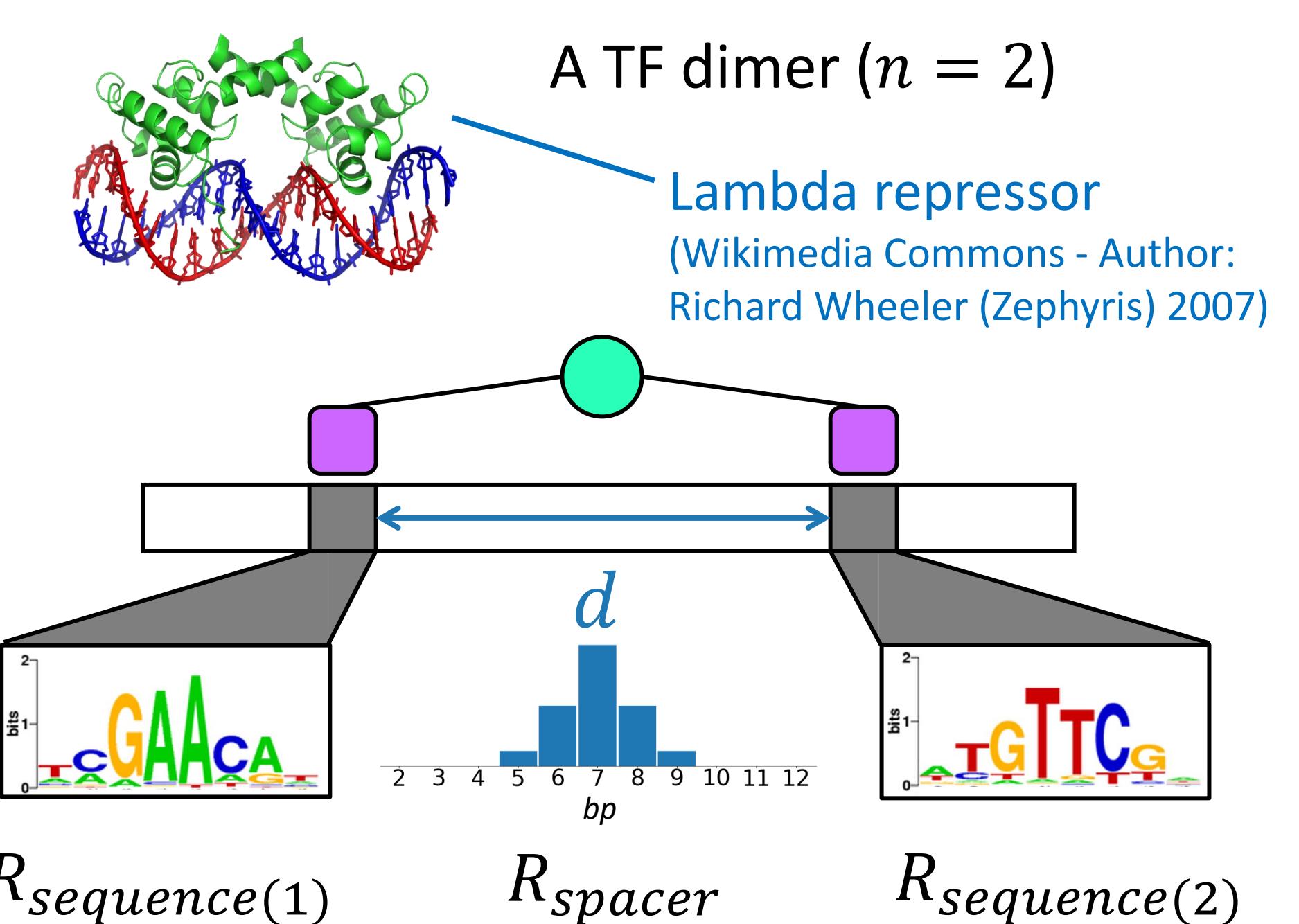
$$-\log_2\left(\frac{\gamma}{G^2}\right) \approx$$

$$\approx R_{\text{sequence}(1)} + R_{\text{sequence}(2)} + R_{\text{spacer}}$$

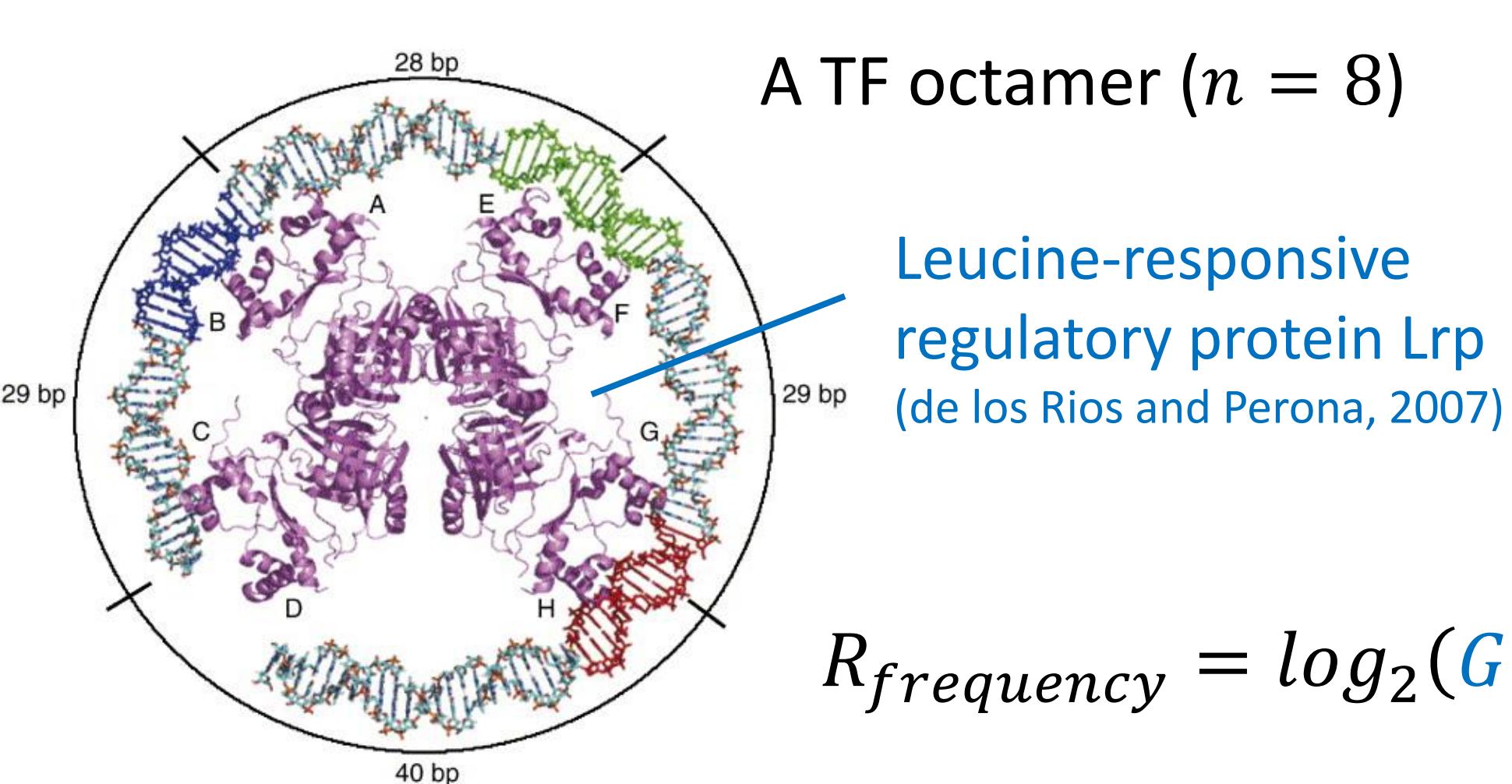
$$R_{\text{sequence}(1)} \leq -\log_2\left(\frac{\gamma}{G}\right)$$

$$R_{\text{sequence}(2)} \leq -\log_2\left(\frac{\gamma}{G}\right)$$

$$\log_2(\gamma) \leq R_{\text{spacer}} \leq \log_2(G)$$



General Theory ($n \geq 1$)



A GENERAL INFORMATION THEORY OF COMPOSITE MOTIFS

(equivalent to Schneider's equation in the special case when $n = 1$)

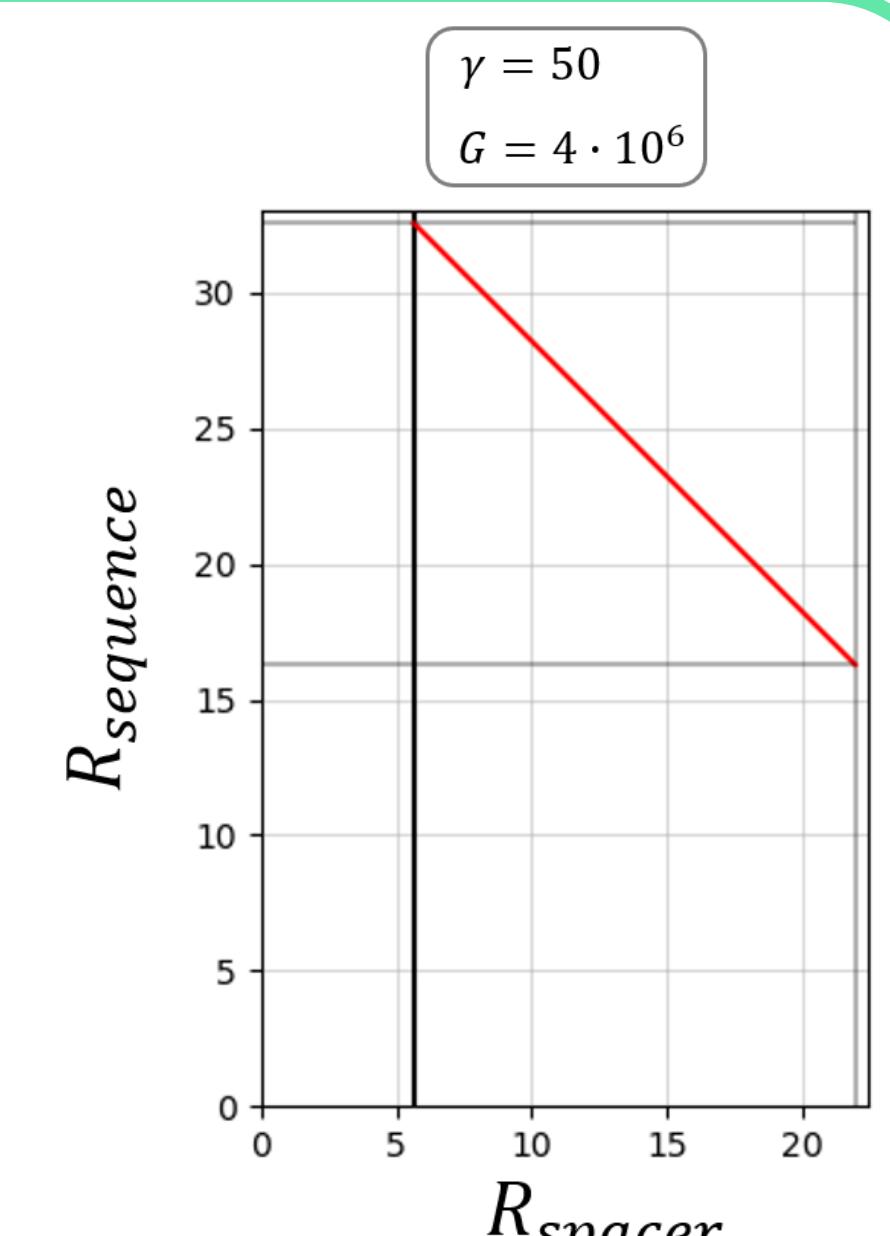
$$\sum_{i=1}^n R_{\text{sequence}(i)} + \sum_{i=1}^{n-1} R_{\text{spacer}(i)} \approx -\log_2\left(\frac{\gamma}{G^n}\right)$$

$$R_{\text{sequence}(i)} \leq -\log_2\left(\frac{\gamma}{G}\right) \forall i \leq n$$

$$\log_2(\gamma) \leq R_{\text{spacer}(i)} \leq \log_2(G) \forall i \leq n-1$$

We can re-write it by redefining the terms as:

$$R_{\text{sequence}} + R_{\text{spacer}} \approx R_{\text{frequency}}$$



Regulator's biophysics

Harmonic oscillator in thermal bath → The distance between recognizers is Gaussian, with variance:

$$\sigma_{\text{protein}}^2 = \frac{k_B T}{\kappa}$$

κ_{opt} : value of κ such that

$$\sigma_{\text{protein}}^2 = \sigma_{\text{targets}}^2$$

Energy dissipation

Minimum energy dissipation per target recognition:

RECRUITMENT PRE-RECRUITMENT

$$k_B T \ln(2)(R_{\text{sequence}} + R_{\text{spacer}}) \text{ joules}$$

Landauer's limit:

$$E_{\min} = k_B T \ln(2) \text{ (joules per bit)}$$

Recruitment-based searches: less thermodynamically efficient, but ≥ 2 possible output states (combinatorial control).

PRE-RECRUITMENT

$$k_B T \ln(2)(R_{\text{sequence}}) \text{ joules}$$

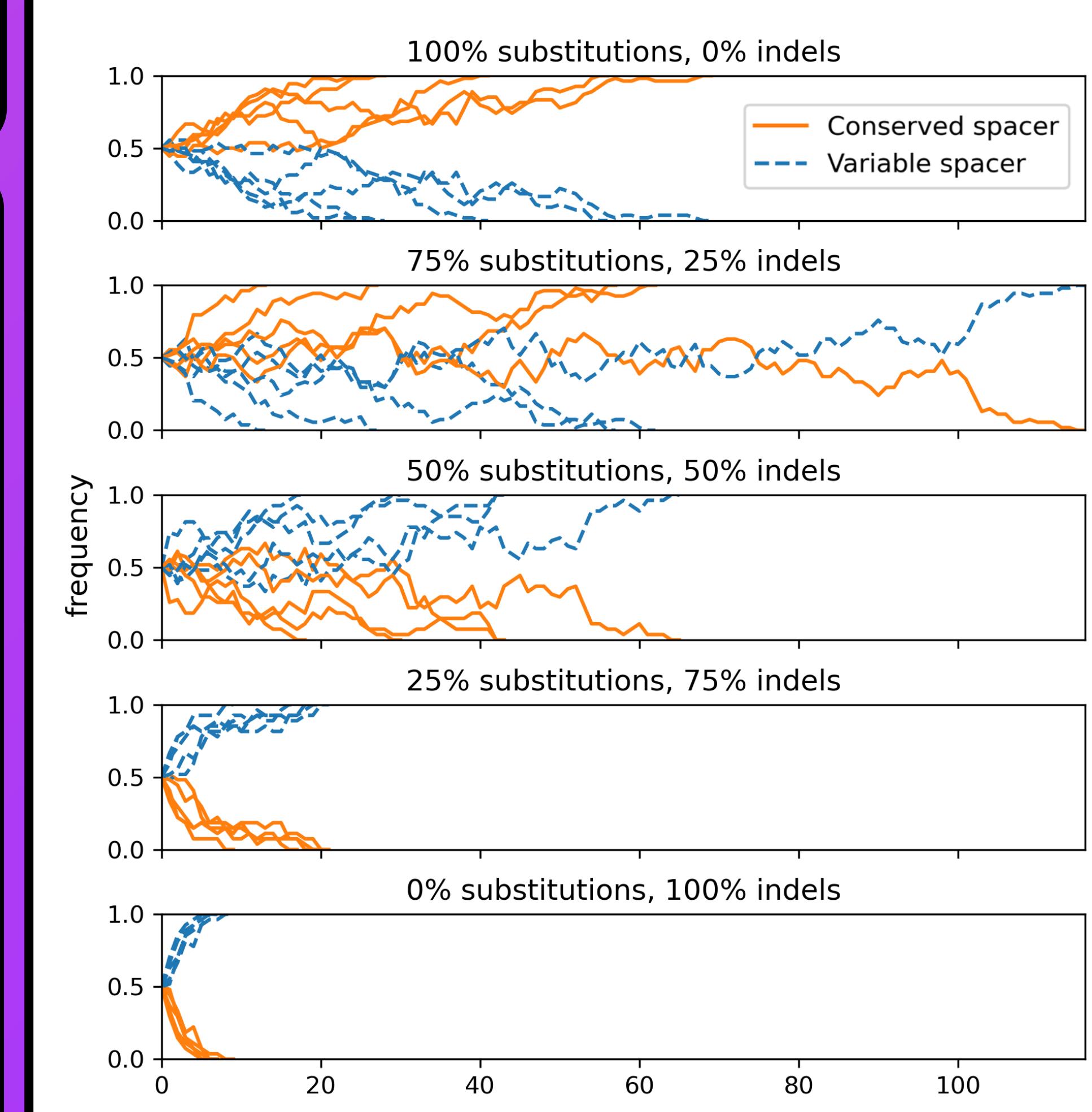
when the flexibility of the protein structure matches the spacer size distribution (e.g., Gaussian spacers: $\sigma_{\text{protein}}^2 = \sigma_{\text{targets}}^2$)

Competing strategies

R_{sequence} VS R_{spacer}
What encoding strategy should be prioritized?
It depends on mutation rates:

substitutions VS indels

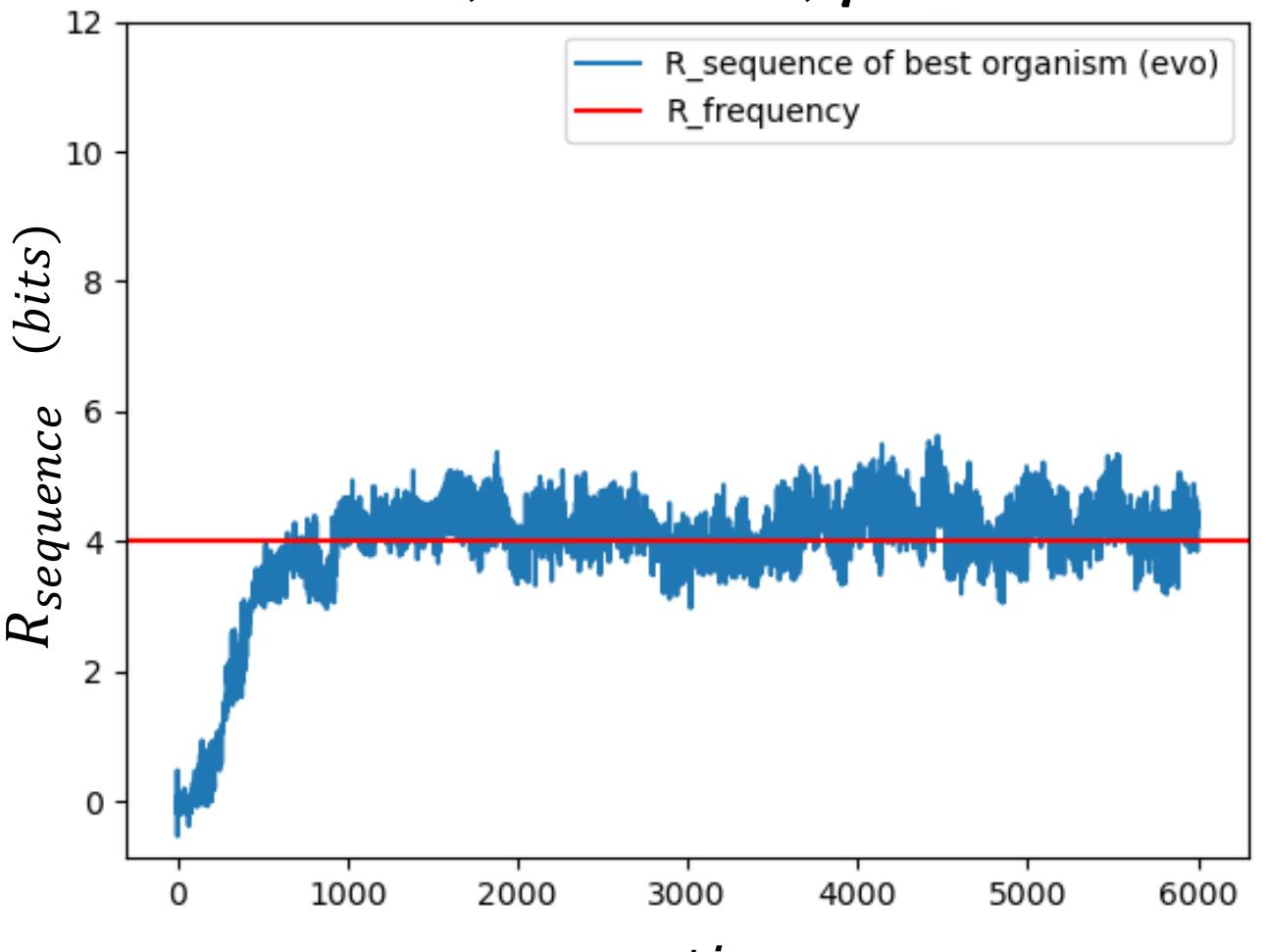
Competition experiments demonstrate the importance of *mutational robustness*.



Evolutionary simulations

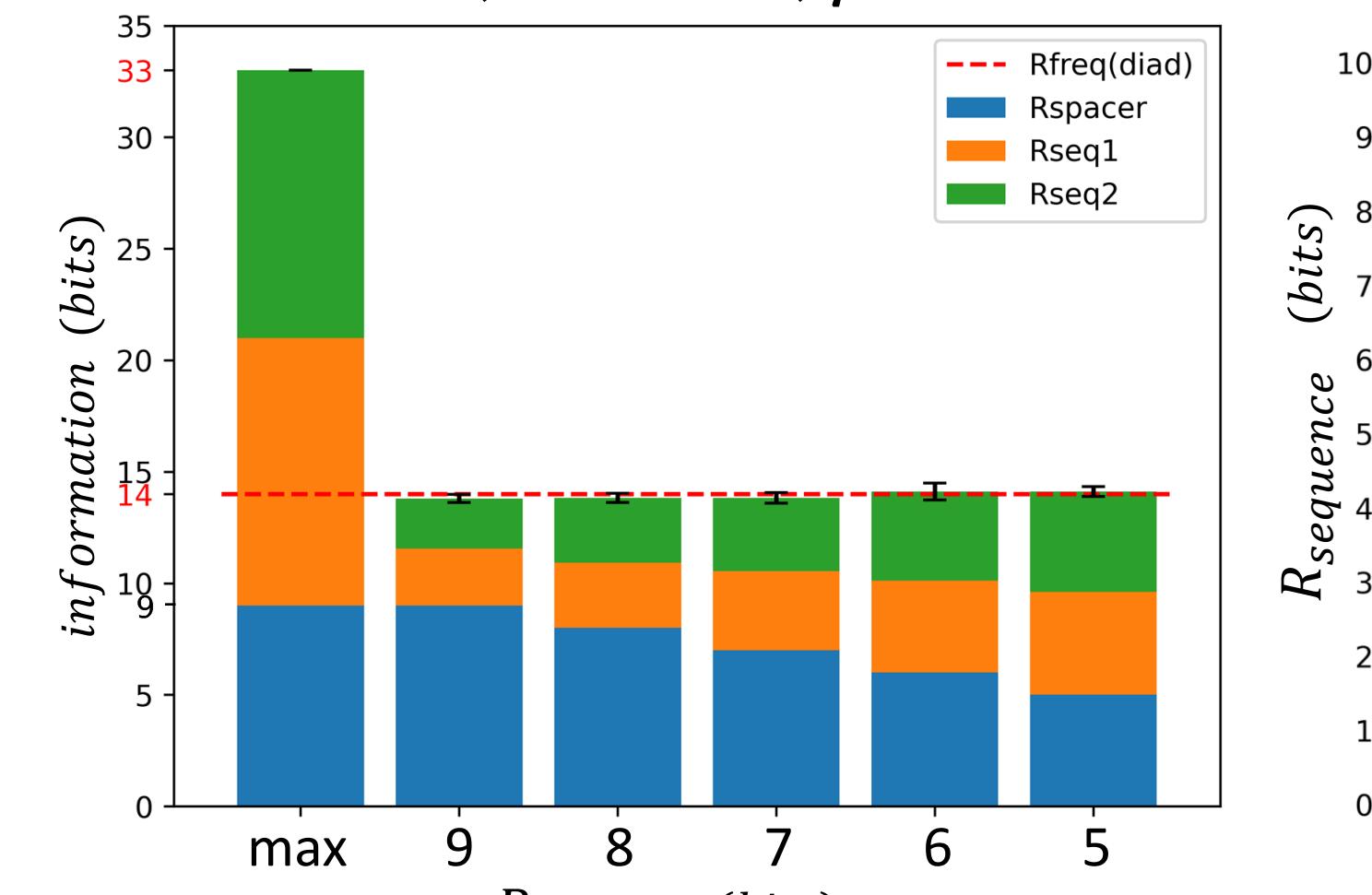
$n = 1$ to reproduce results from (Schneider, 2000)

$$n = 1, G = 256, \gamma = 16$$



$n = 2$ to validate the relationship between R_{sequence} and R_{spacer} in composite motifs.

$$n = 2, G = 512, \gamma = 16$$



The proteins quickly evolve their flexibility to match the variability in the targets' spacer.

