Homeostatic Adaptation of Optimal Population Codes under Metabolic Stress

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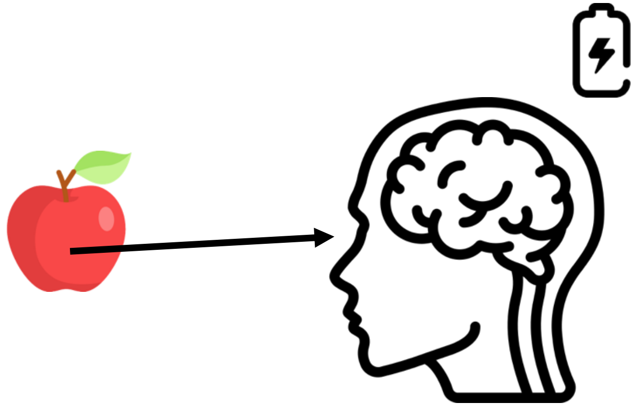
How does caloric deprivation affect neural population codes?

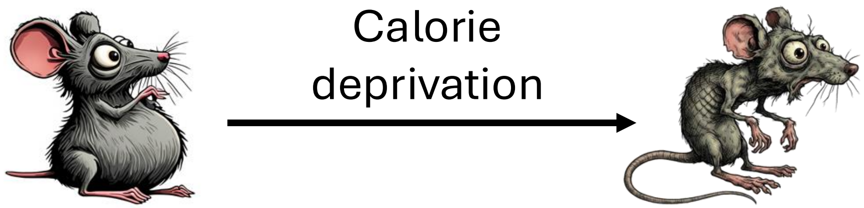
Motivation



Processing visual input requires a considerable amount of energy.

What happens to processing when energy is limited?

2–3 weeks: 15% loss in body weight



In neocortex (L2/3)

- ~29% reduction in ATP usage
- Firing rates are maintained
- Flattened tuning curves

[Padamsey et al., 2022]

Is there any normative model that can describe this adaptation to metabolic stress?

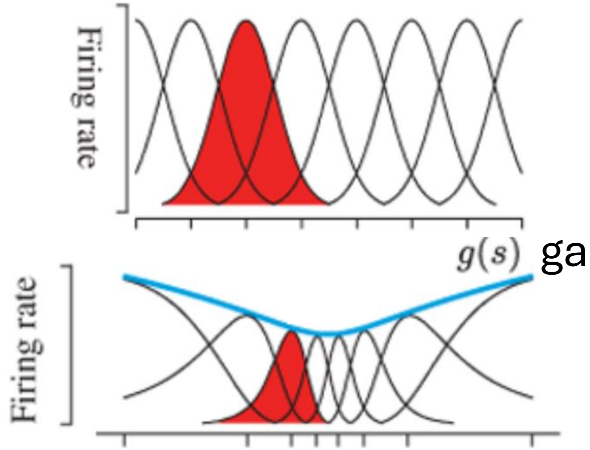
Homeostatic Constrained Optimization

$$\underset{h_1(\cdot),\ldots,h_N(\cdot)}{\operatorname{argmax}} \int p(s) f\left(FI(s;E)\right) \mathrm{d}s, \quad \text{s.t.} \int p(s) h_n(s)\, \mathrm{d}s = R_n,\ \forall n$$

Optimize tuning curves to **transmit information efficiently** w.r.t. **energy** while **maintaining FR**.

Accurate but not explainable due to requirement of numerical solvers

[Ganguli & Simoncelli, 2010]



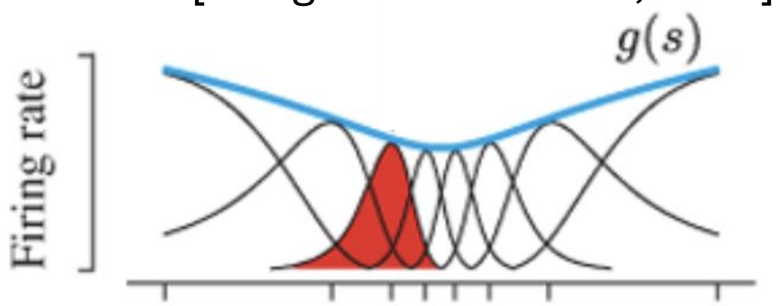
gain

$d(s)$
(centers and density)

Need simplifying assumptions:
Gaussian population, gain and density

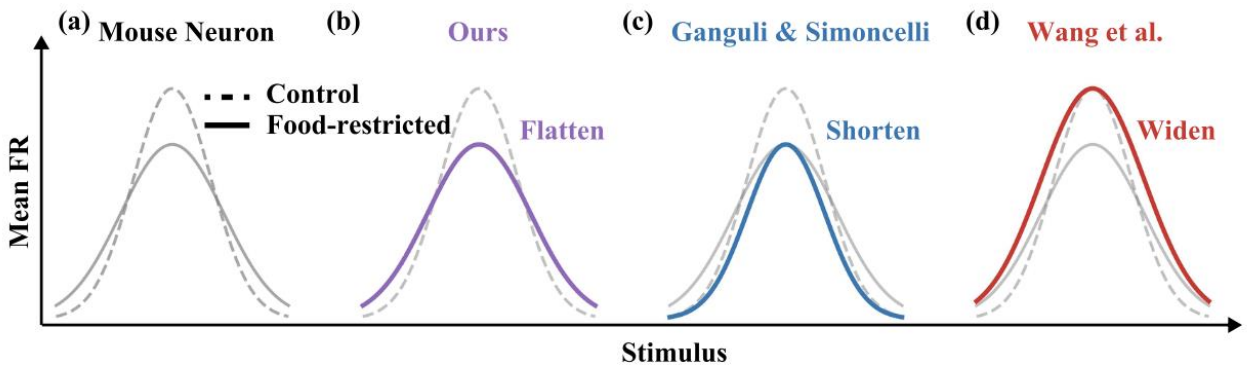
infomax: $f(x) = \log(x)$ → L0 norm
discrimax: $f(x) = -x^{-1}$ → L2 norm

[Ganguli & Simoncelli, 2010]



Comparison to Prior Work

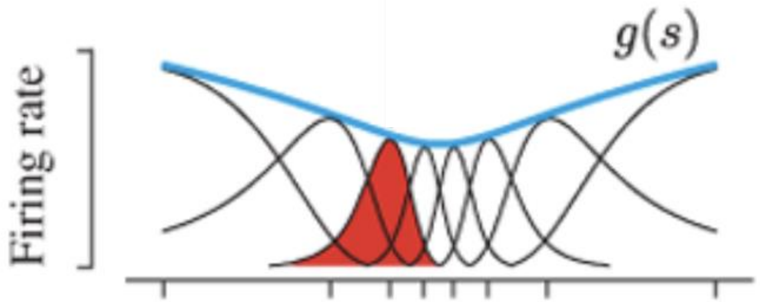
Works	Constraints	Constraints under Tiling	Noise	Low Energy
Ganguli & Simoncelli	mean FR population size	$\int p(s)g(s)\mathrm{d}s = R$ $\int d(s)\mathrm{d}s = N$	Poisson	$R\downarrow$, shortens (N fixed)
Wang et al.	max FR total FI states	$g(s) \propto 1$ $\int \sqrt{g(s)d(s)^2}\mathrm{d}s = C$	Poisson or Gaussian	$C\downarrow$, widens (g fixed)
Ours	energy approx. homeostasis	$\int p(s)g(s)^{\alpha}\mathrm{d}s = E$ $\frac{g(s)}{d(s)} = \frac{R(s)}{p(s)}$	Energy-dependent Dispersed Poisson	$E\downarrow$, flattens ($R(s)$ fixed)



Wrong constraints → Wrong adaptation!

Ganguli & Simoncelli, NeurIPS 2010
Wang et al., Neural Computation 2016

Proposed Model



- Two novel constraints: homeostasis, energy budget
- Noise-energy trade-off gives 3 new parameters (E, alpha, eta) that we ground in biophys sim

$$\underset{g(\cdot),d(\cdot)}{\operatorname{argmax}} \int p(s) f\left(\eta_\kappa(E)^{-1} g(s) d(s)^2\right) \mathrm{d}s,$$

Approximate information in gain and density **(Append. A)**

$$\text{s.t.} \quad p(s)\frac{g(s)}{d(s)} = R(s)$$

Approximate FR homeostasis **(Prop. C.1)**

$$\int p(s) g(s)^\alpha \mathrm{d}s = E, \quad \text{where } \alpha \geq 1.$$

Energy limit

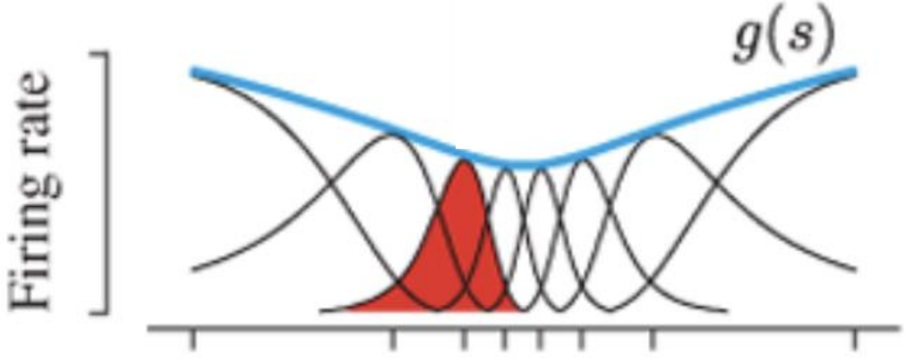
Model Details --- energy limit

$$\int p(s)g(s)^{\alpha}\mathrm{d}s = E, \quad \text{where } \alpha \geq 1$$

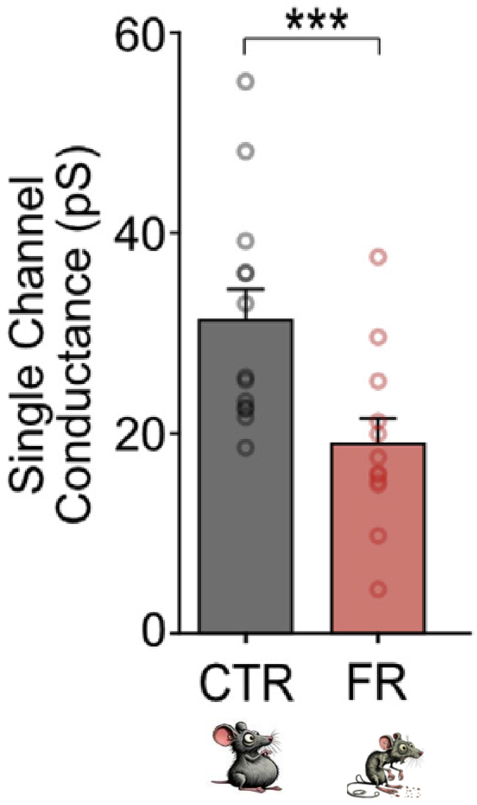
Expected ATP in natural scenes

Flattened TCs are less excitable, have lower peaks

DOF



$d(s)$
(centers and density)



Padamsey et al., Neuron 2022

Analytical Solution

$$\underset{g(\cdot),d(\cdot)}{\text{argmax}} \int p(s) f\left(\eta_\kappa(E)^{-1} g(s) d(s)^2\right) \mathrm{d}s,$$

$$\text{s.t.} \quad p(s)\frac{g(s)}{d(s)} = R(s)$$

$$\int p(s) g(s)^\alpha \mathrm{d}s = E, \quad \text{where } \alpha \geq 1.$$

infomax: $f(x) = \log(x)$ → L0 norm
discrimax: $f(x) = -x^{-1}$ → L2 norm

	infomax	**discrimax**	**L_p error, $p = -2\beta$**
Optimized function	$f(x) = \log x$	$f(x) = -x^{-1}$	$f(x) = -x^\beta,\ \beta < \frac{\alpha}{3}$
Density (tuning width)$^{-1}$ $d(s)$	$E^{\frac{1}{\alpha}} R(s)^{-1} p(s)$	$\propto E^{\frac{1}{\alpha}} R(s)^{\frac{-\alpha-1}{\alpha+3}} p(s)^{\frac{\alpha+1}{\alpha+3}}$	$\propto E^{\frac{1}{\alpha}} R(s)^{\frac{\alpha-\beta}{3\beta-\alpha}} p(s)^{\frac{\beta-\alpha}{3\beta-\alpha}}$
Gain $g(s)$	$E^{\frac{1}{\alpha}}$	$\propto E^{\frac{1}{\alpha}} R(s)^{\frac{2}{\alpha+3}} p(s)^{\frac{-2}{\alpha+3}}$	$\propto E^{\frac{1}{\alpha}} R(s)^{\frac{2\beta}{3\beta-\alpha}} p(s)^{\frac{-2\beta}{3\beta-\alpha}}$
Fisher information $FI(s)$	$\propto \frac{E^{\frac{3}{\alpha}} p(s)^2}{\eta_\kappa(E) R(s)^2}$	$\propto \frac{E^{\frac{3}{\alpha}} p(s)^{\frac{2\alpha}{\alpha+3}}}{\eta_\kappa(E) R(s)^{\frac{2\alpha}{\alpha+3}}}$	$\propto \frac{E^{\frac{3}{\alpha}} p(s)^{\frac{-2\alpha}{3\beta-\alpha}}}{\eta_\kappa(E) R(s)^{\frac{2\alpha}{\alpha-3\beta}}}$
Discriminability bound $\delta_{\min}(s)$	$\propto E^{\frac{-3}{2\alpha}} p(s)^{-1}$	$\propto E^{\frac{-3}{2\alpha}} p(s)^{\frac{-\alpha}{\alpha+3}}$	$\propto E^{\frac{-3}{2\alpha}} p(s)^{\frac{\alpha}{3\beta-\alpha}}$

E, α, η_κ can be found by simulation **(Sec. 4)**, but first...!

Ganguli & Simoncelli, NeurIPS 2010
Wang et al., Neural Computation 2016

Relation to Existing Models

We introduce novel constraints!

Works	Constraints	Constraints under Tiling	Noise	Low Energy
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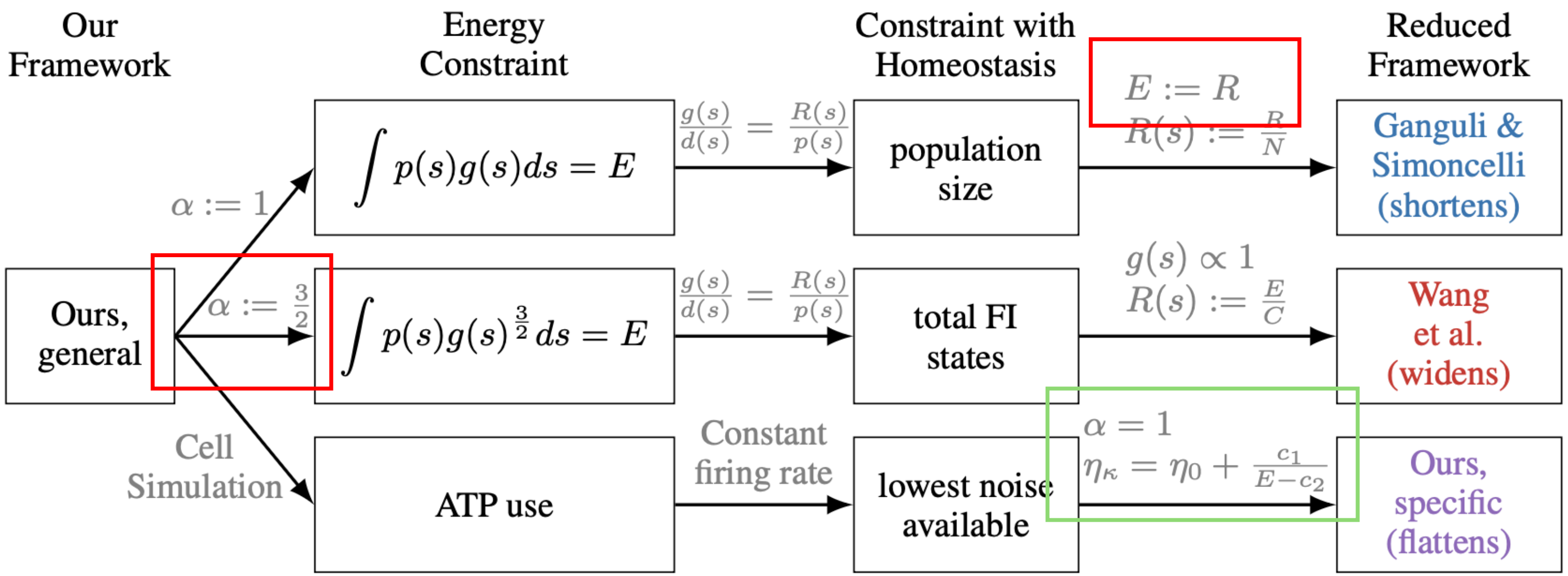
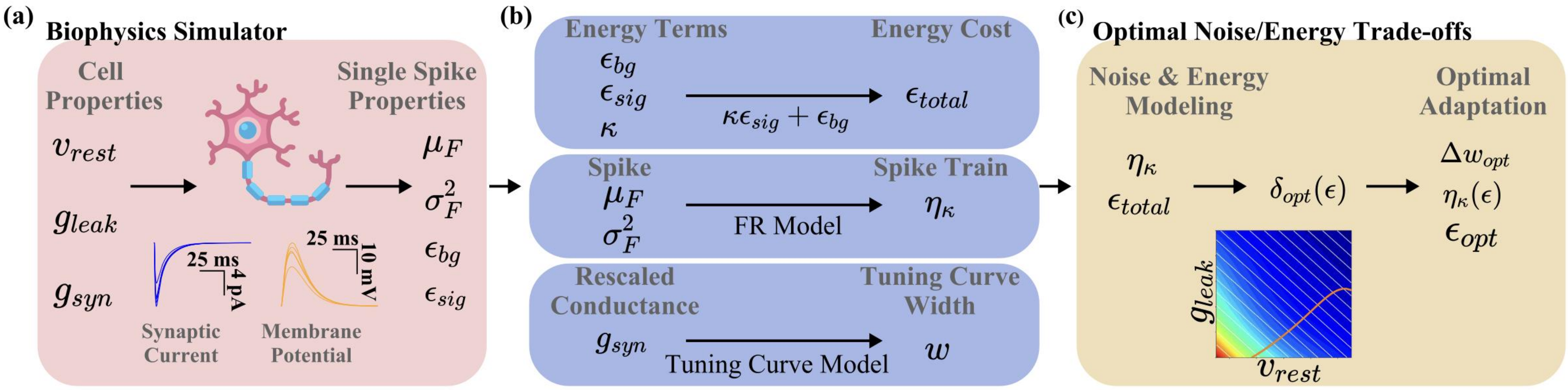
We can generalize to other methods although using novel constraints!



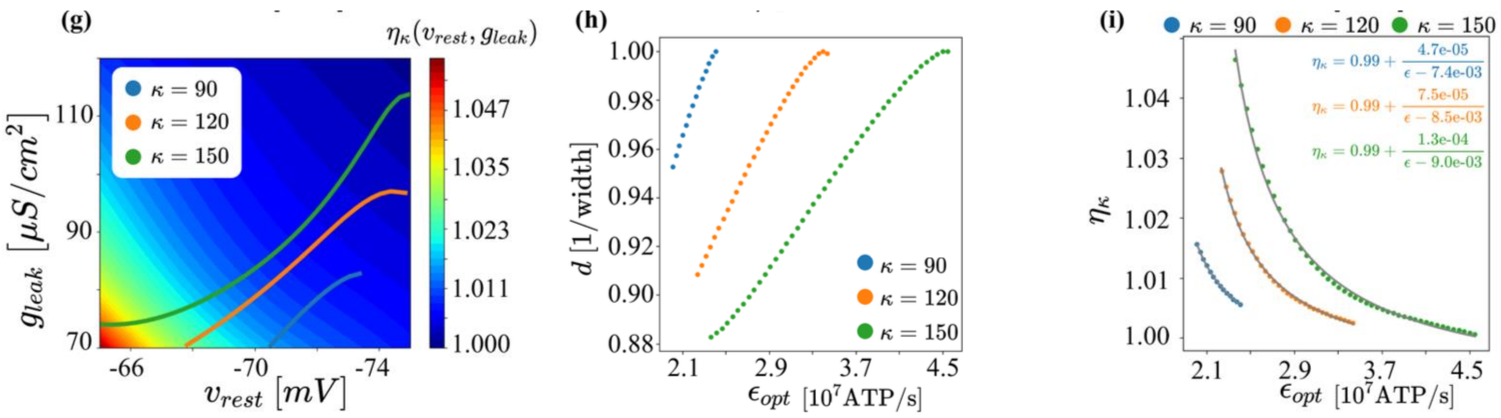
How to set the parameters (α and η_κ)?

- We find the noise/energy trade-off curve by simulation single-compartment neuron model (NEURON package).



How to set the parameters (α and η_κ)?

- We find
  - The noise-energy trade-off curves depend on the input signal activity
  - The linear relation between density and energy => $\alpha = 1$
  - $\eta_\kappa = \eta_0 + c_1/(\epsilon - c_1)$



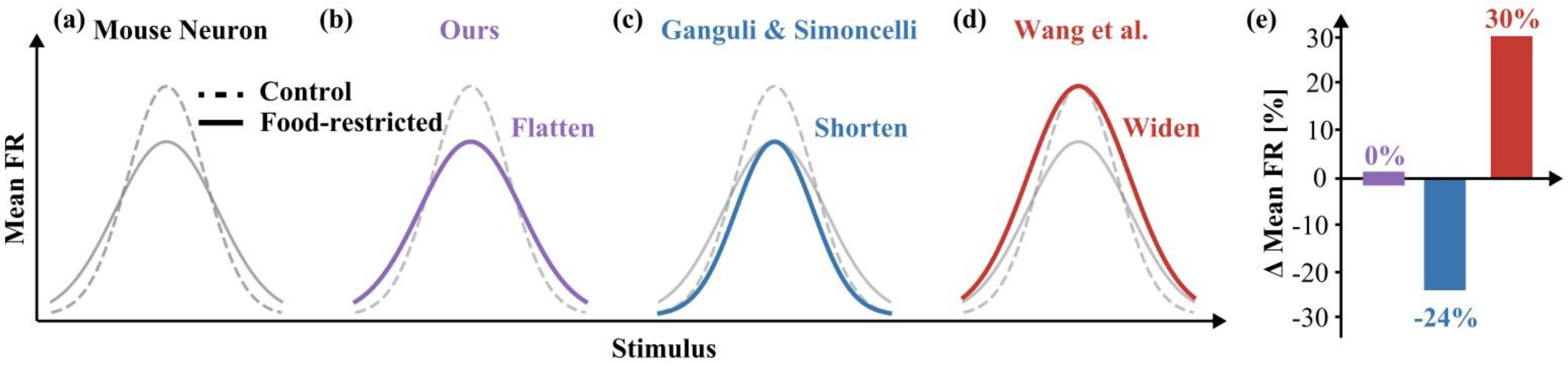
Compare to Experimental Data

Simulation-driven parameters

$$\alpha = 1$$
$$\eta_\kappa = \eta_0 + c_1/(\epsilon - c_1)$$

Analytical solution

	infomax
Optimized function	$f(x) = \log x$
Density (tuning width)$^{-1}$ $d(s)$	$E^{\frac{1}{\alpha}} R(s)^{-1} p(s)$
Gain $g(s)$	$E^{\frac{1}{\alpha}}$



Conclusion

$$\underset{g(\cdot),d(\cdot)}{\operatorname{argmax}} \int p(s) f\left(\eta_\kappa(E)^{-1} g(s) d(s)^2\right) \mathrm{d}s,$$

$$\text{s.t.} \quad p(s)\frac{g(s)}{d(s)} = R(s)$$

$$\int p(s) g(s)^\alpha \mathrm{d}s = E, \quad \text{where } \alpha \geq 1.$$

- We introduce **two mathematically-tractable constraints** that more accurately characterize real neurons’ response to metabolic stress.
- Our framework **generalizes previous models**, and can recover disparate results from the literature
- **Biophysical simulation** grounds key parameters of our model.