

Cell Polarization, a review of Models and Experiments

Jilkine A, Edelstein-Keshet L (2011) A
Comparison of Mathematical Models for
Polarization of Single Eukaryotic Cells in
Response to Guided Cues.

PLoS Comput Biol 7(4): e1001121.

Universal features of polarizing cells

1. Ability to sense both steep and shallow external gradients (as small as 1%–2%) in vast range of concentrations. Polarization leads to an *amplification* of this asymmetry to some macroscopic level.
2. Remain *sensitive to new stimuli*, and can reorient when the stimulus gradient is changed.
3. Polarity maintained after stimulus is removed (*maintenance*) – may require cytoskeleton.

Additional features of some cells

1. *Spontaneous polarization*, in absence of spatial cues.
2. *Adaptation*: a persistent response to a gradient stimulus, but transient response to a spatially uniform stimulus.
3. Response to multiple stimuli: either *multiple “fronts”* or a *unique axis of polarity*.
4. Pseudopods continually extended and retracted. Reorient by splitting a pseudopod, one part becoming dominant.

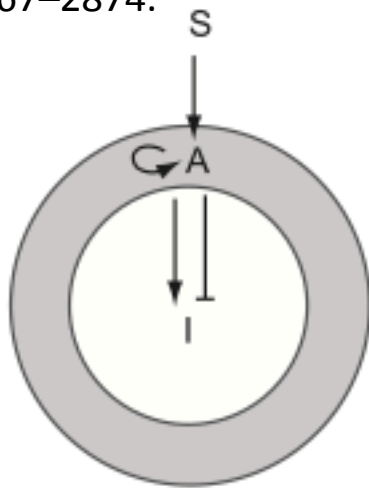
Cell type comparisons

Cell type	Polarization Behaviors	Scale
Budding yeast	Spontaneous polarization, unique axis of polarity	Size: 5 μm , TP: 3 min
<i>D. discoideum</i>	Gradient sensing (1% and up), adaptation (Lat), spontaneous polarization, high amplification, reorientation, maintenance, multiple fronts (Lat), unique axis (WT)	Size: 10–20 μm , TP: 30–60 s, speed: 3–15 $\mu\text{m}/\text{min}$
Fibroblasts	Gradient sensing, reorientation	Size: 50–150 μm , TP: 30–50 min, speed: 1 $\mu\text{m}/\text{min}$
Keratocytes	Spontaneous polarization, maintenance	Size: 10 μm (fragments), 30–40 μm (cells), speed: 10–40 $\mu\text{m}/\text{min}$,
Neutrophils	Gradient sensing, spontaneous polarization, high amplification, reorientation, unique axis (WT)	Size: 10 μm , TP: 30 s, speed: 10–20 $\mu\text{m}/\text{min}$
Neurons	Attractive/repulsive turning, gradient detection, adaptation	

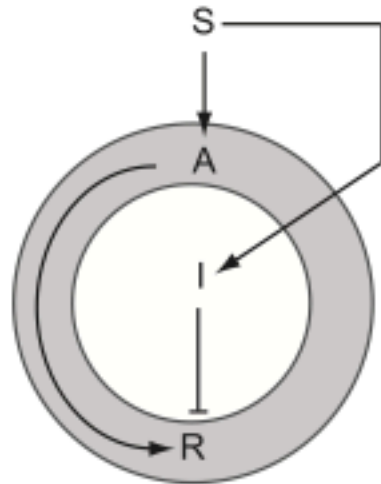
Stimuli and signaling proteins

Cell type	Feedback Loops	Stimulus	Cytoskeleton
Budding yeast	Cdc42→Cdc24→Cdc42, Cdc42→actin→Cdc42	Bud1	Actin (MO)
<i>D. discoideum</i>	Amplification upstream of PI3K	cAMP	Actin (MO)
Fibroblasts	Cdc42→Rac→RhoA	PDGF, fibronectin, interleukins	Actin, MT, FA
Keratocytes		Mechanical	Actin
Neutrophils	Front/back mutual inhibition PIP3→actin→PIP3	fMLP, interleukins, others	Actin
Neurons	Rac/Rho mutual inhibition	Netrins, semaphorins, ephrins	Actin, MT

Lateral Inhibition, Turing
 Meinhardt (1999). J Cell Sci 112:
 2867–2874.



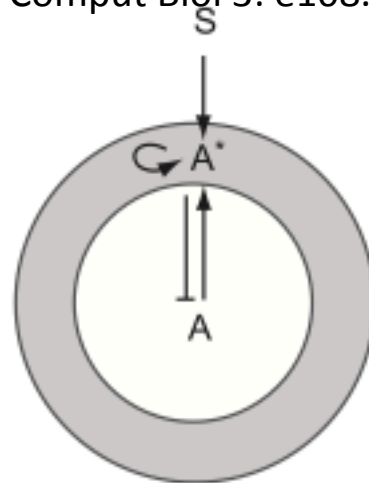
(a)



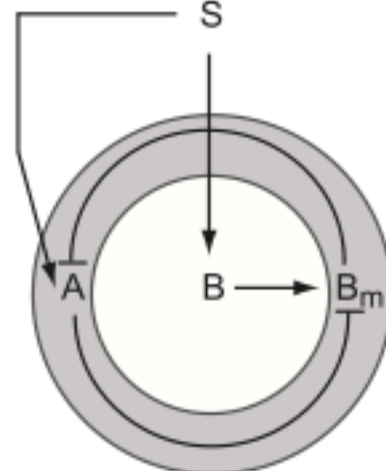
(d)

LEGI
 Levchenko A, Iglesias P (2002).
 Biophys J 82: 50–63

Substrate depletion
 Otsuji et al. (2007) PLoS
 Comput Biol 3: e108.



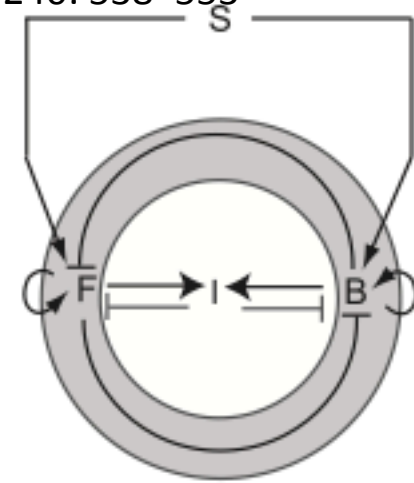
(b)



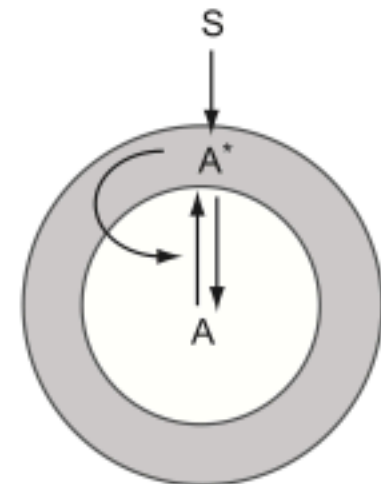
(n)

Balanced inactivation
 Levine H, Kessler DA, Rappel WJ
 (2006) PNAS 103: 9761–9766

Turing, mutual inhibition
 Narang A (2006) J Theor Biol
 240: 538–553



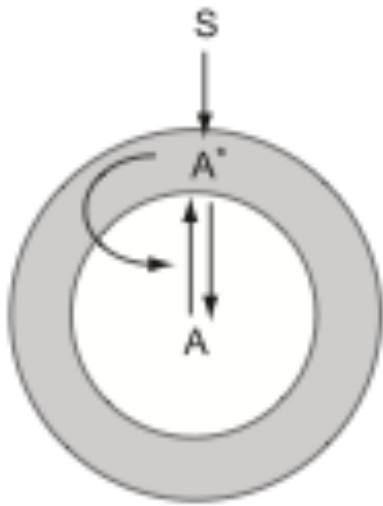
(c)



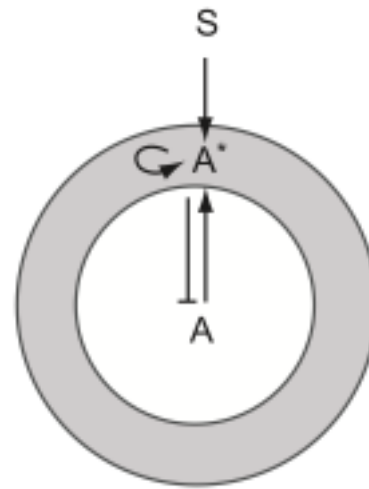
(g)

Wave-pinning
 Mori Y, Jilkine A, LEK (2008)
 Biophys J 94: 3684–3697

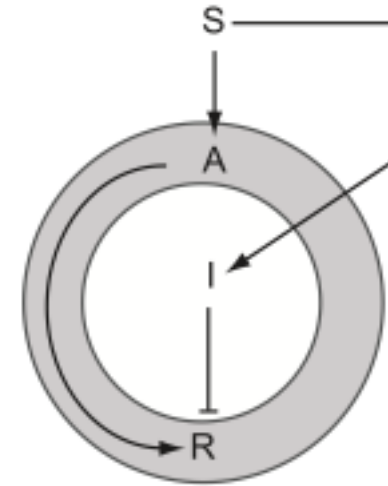
Testing four models



Wave-Pinning



Goryachev



Otsuji

LEGI

Types of models

$$\frac{\partial u}{\partial t} = D_u \frac{\partial^2 u}{\partial x^2} + f(u, v),$$

$$\frac{\partial v}{\partial t} = D_v \frac{\partial^2 v}{\partial x^2} + g(u, v),$$

- Wave-pining

$$f(u,v) = -g(u,v) = v \left(k_0 + \frac{\gamma u^2}{K^2 + u^2} \right) - \delta u.$$

- Otsuji

$$f(u,v) = -g(u,v) = a_1 \left[v - \frac{u+v}{(a_2 s(u+v) + 1)^2} \right],$$

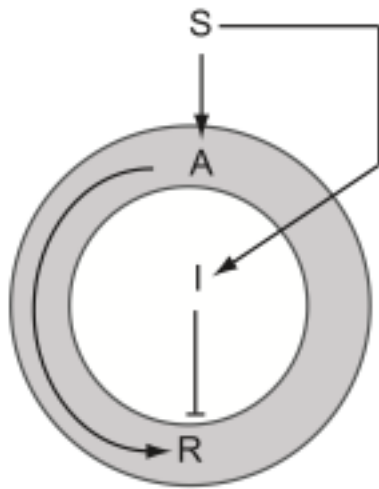
- Goryachev

$$f(u,v) = -g(u,v) = \alpha E_c u^2 v + \beta E_c uv - \gamma u, \quad E_c = \frac{E_c^0}{1 + \int_S f(u) ds}.$$

- LEGI: see over

LEGI

$$\frac{\partial A}{\partial t} = k_A S(t, x) - k_{-A} A,$$



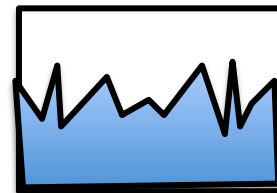
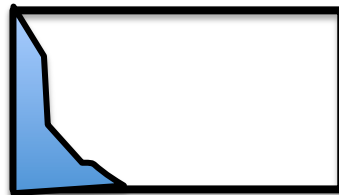
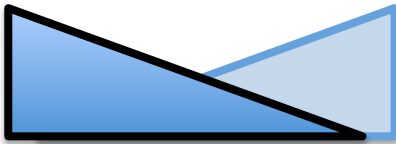
$$\frac{\partial I}{\partial t} = D \frac{\partial^2 I}{\partial x^2} + k_I S(t, x) - k_{-I} I,$$

$$\frac{\partial R}{\partial t} = k_R A (R_T - R) - k_{-R} I R,$$

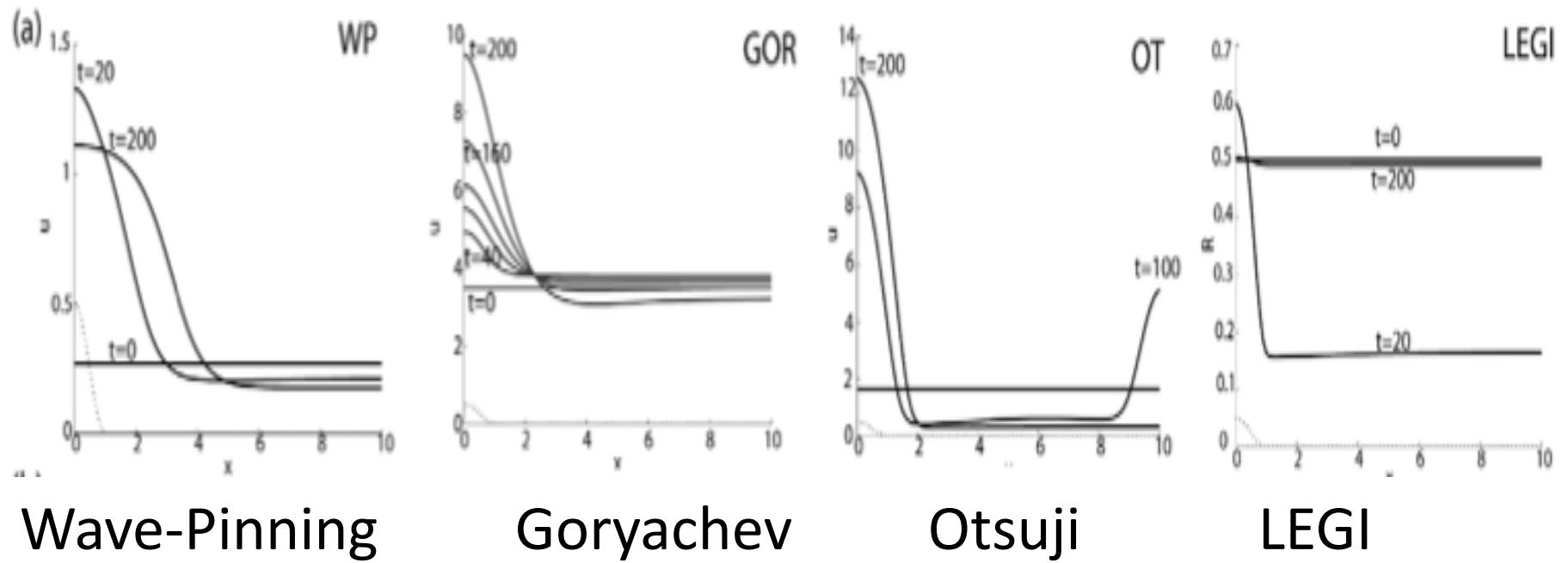
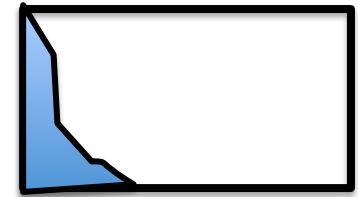
Stimuli

$$\frac{\partial u}{\partial t} = D_u \frac{\partial^2 u}{\partial x^2} + f(u, v) + k_S v,$$

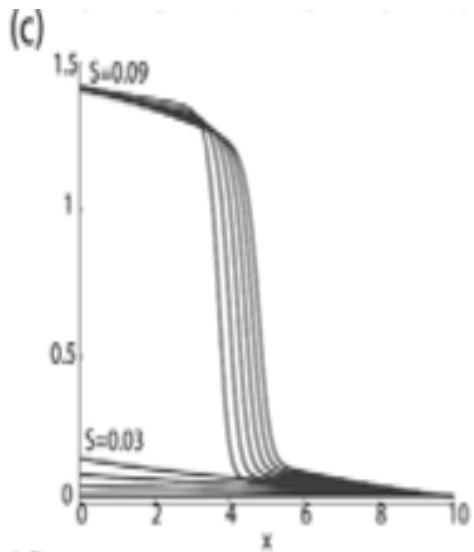
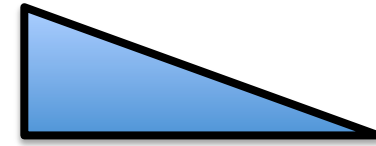
$$\frac{\partial v}{\partial t} = D_v \frac{\partial^2 v}{\partial x^2} - f(u, v) - k_S v,$$



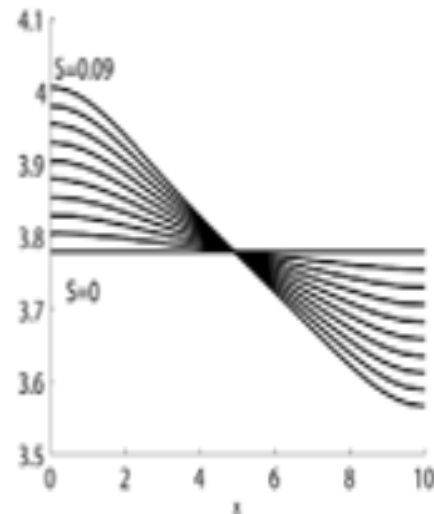
Single localized stimulus at left edge of the cell



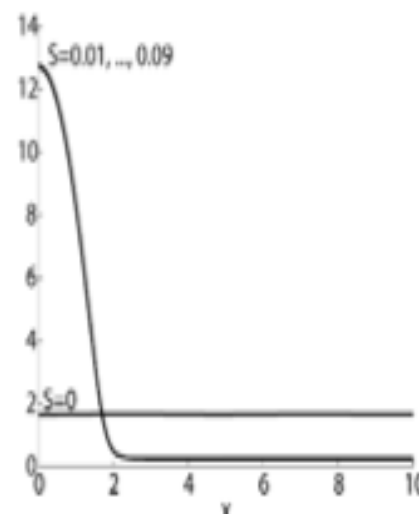
Gradient stimulus



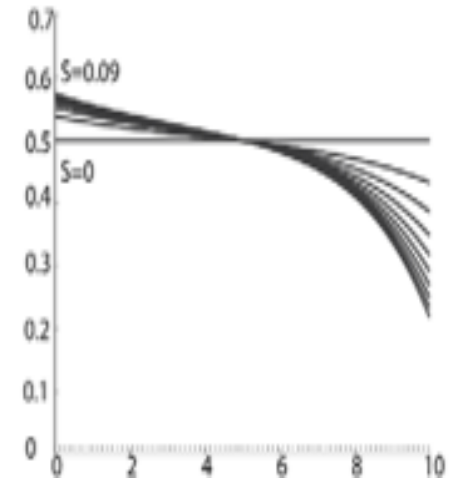
Wave-Pinning



Goryachev

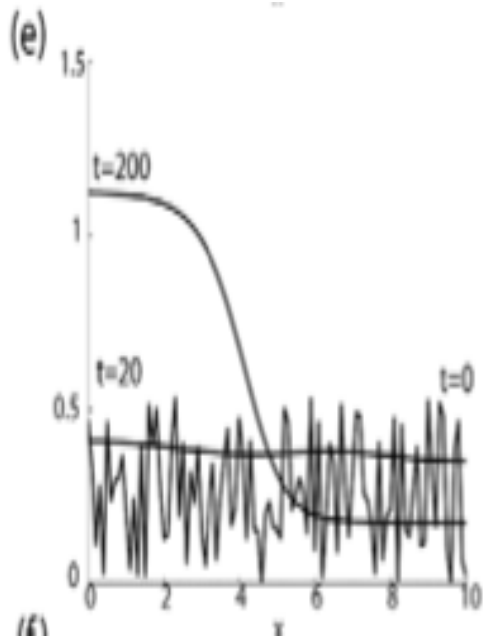
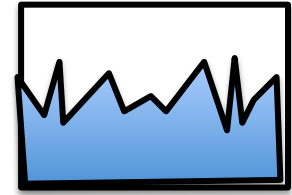


Otsuji

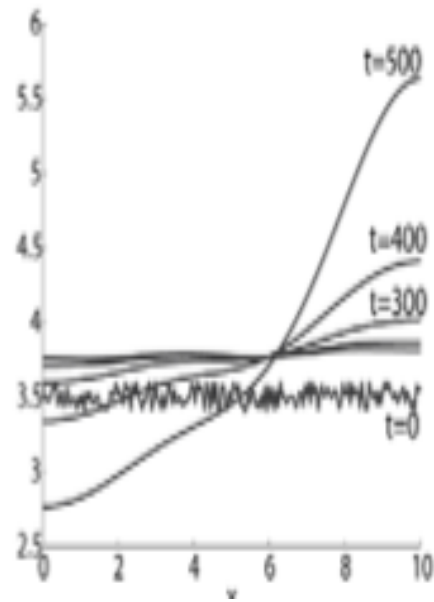


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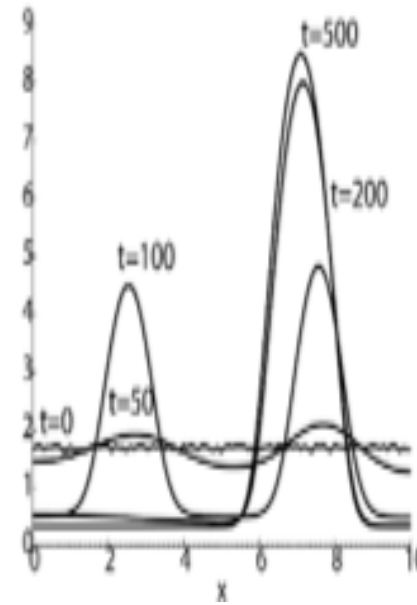
Noisy initial conditions



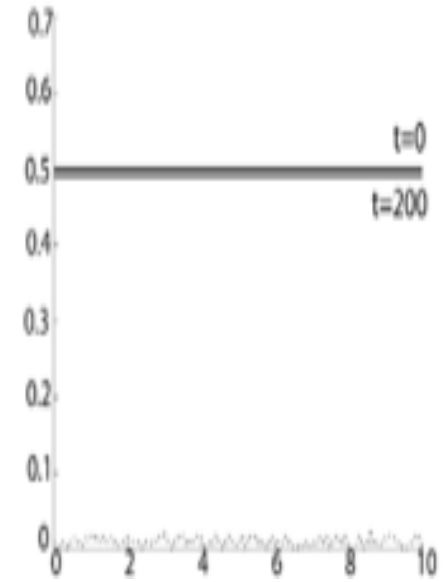
Wave-Pinning



Goryachev

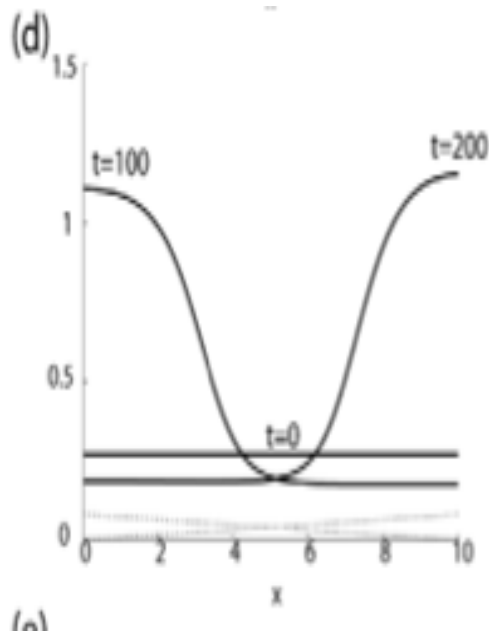
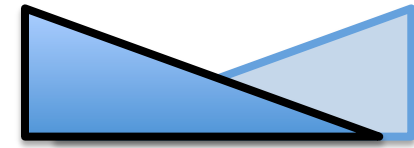


Otsuji

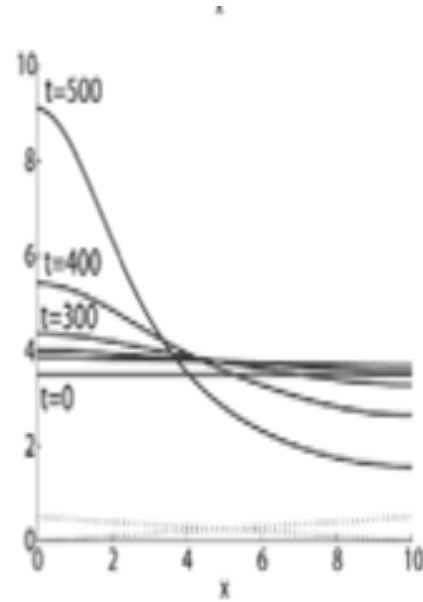


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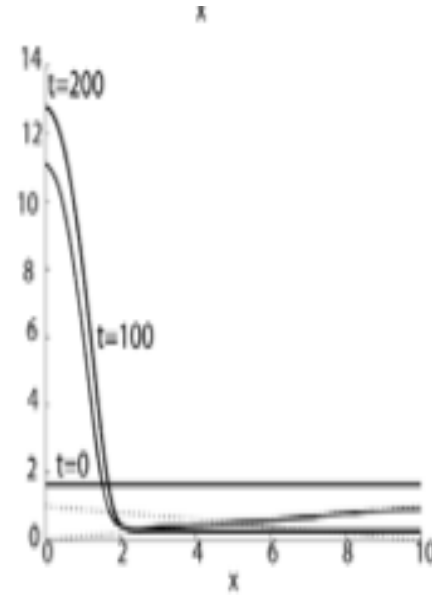
Gradient + reversal



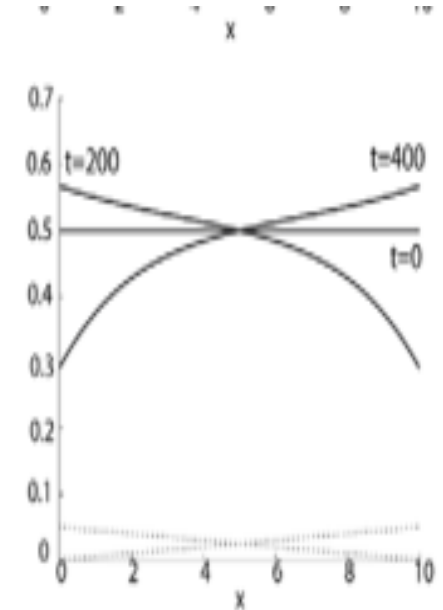
Wave-Pinning



Goryachev



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In such Turing-type models, the pattern will not reverse when a new gradient of opposite polarity is applied

Features that models can explain

Behavior	"Turing Type"	Wave-Based	Gradient Sensing
Maintenance of polarity	Yes	Yes	No
Multi-stimuli response	Yes (transient)	Yes (long time-scale)	Yes
High amplification	Yes	Yes	No
Adaptation	No	No	Yes
Spontaneous polarization	Yes	Yes	No
Reversible asymmetry	No	Yes	Yes