LPA: Finer Points

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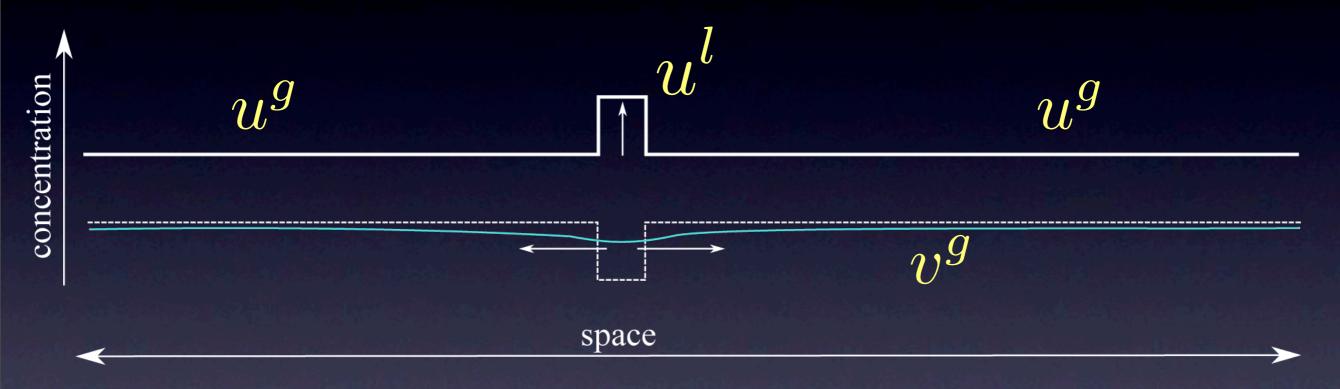
Topics of Discussion

- Relationship between LPA results and Turing analysis.
- How the LPA informs knowledge of long term evolution of spatial patterns.

LPA Setup

Slow Diffusing $\frac{\partial u}{\partial t}(x,t) = f(u,v;p) + \epsilon u_{xx}$ Fast $\frac{\partial v}{\partial t}(x,t) = g(u,v;p) + Dv_{xx}$ Diffusing

Local Perturbation Analysis



 'g' indicates a global variable, 'l' indicates local.

LP - System

Global:
$$\dfrac{du^g}{dt}(x,t)=f(u^g,v^g;p),$$
 Global: $\dfrac{dv^g}{dt}(x,t)=g(u^g,v^g;p),$ Local: $\dfrac{du^l}{dt}(x,t)=f(u^l,v^g;p)$

LP Perturbation Restriction

 The applied 'local' perturbation can be of ARBITRARY HEIGHT, but it must be of SMALL AREA.

Why?

Consider:
$$\frac{dv^g}{dt}(x,t) = g(u,v^g;p)$$

• Since v^g is spatially homogeneous, integrate.

$$\frac{dv^g}{dt} = \frac{1}{2} \int_{-1}^{1} g(u, v; p) \, dx$$

Continued

$$\frac{dv^g}{dt} = \frac{1}{2} \int_{|x| > \epsilon} g(u, v^g; p) \, dx + \int_{|x| < \epsilon} u \approx u^l$$

Away from the perturbation

Near Perturbation

- Now assume,
 - \bullet ϵ is small
 - $\bullet \ \overline{g(u^l, v^g; p)} \sim O(1)$

Then

$$\frac{du^g}{dt} \approx g(u^g, v^g; p) + \epsilon(g(u^l, v^g; p) - g(u^g, v^g; p))$$
 Small

- So those two assumptions are enough to ensure the equation for \boldsymbol{v}^g is valid.
- Together, they imply the applied perturbation must be of SMALL AREA.

LPA vs Linearization Methods

- Well mixed and Turing analysis require a perturbation to be small in height, but spatially spread.
- LPA requires a perturbation of SMALL AREA, but it can be tall!

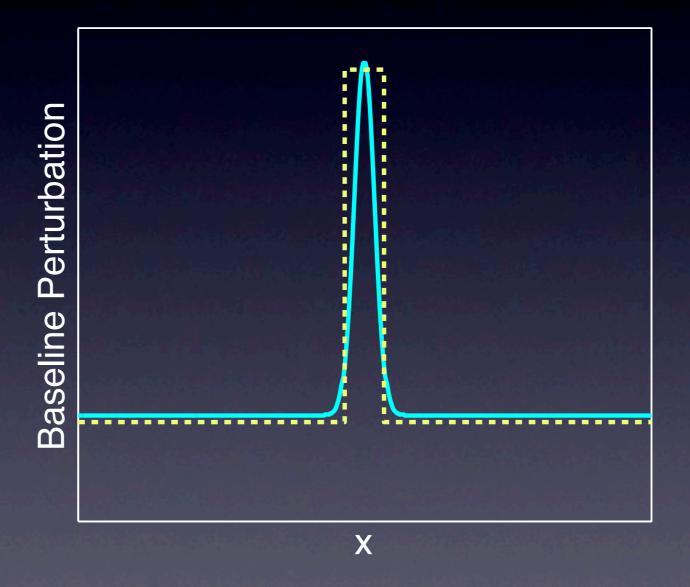
LPA - Linear and Nonlinear stability

- The LPA recovers stability properties of the
 - I. Well mixed system previously discussed
 - 2. Turing system to be discussed

Properties of a Local Perturbation

 $\delta-$ function like

$$\delta_{\sigma} = \exp\left(\frac{x^2}{\sigma^2}\right)$$



Our local perturbation is akin to a delta function

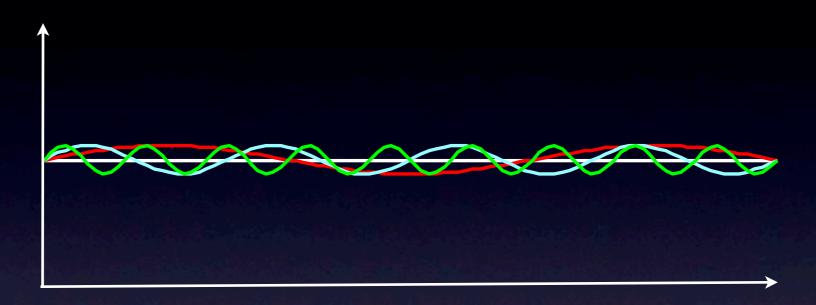
Frequency Spectrum

$$\mathcal{F}[\delta_{\sigma}](k) = \sqrt{\sigma k} \exp(-\sigma^2 k^2)$$

- The spatially local perturbation has a broad Fourier spectrum.
- In the infinitely localized limit, the delta function is the superposition of all wave numbers:

$$\mathcal{F}[\delta](k) = 1$$

Implication



- The LPA tests stability against all wave numbers at once.
- In this way it provides a wave number independent Turing analysis.

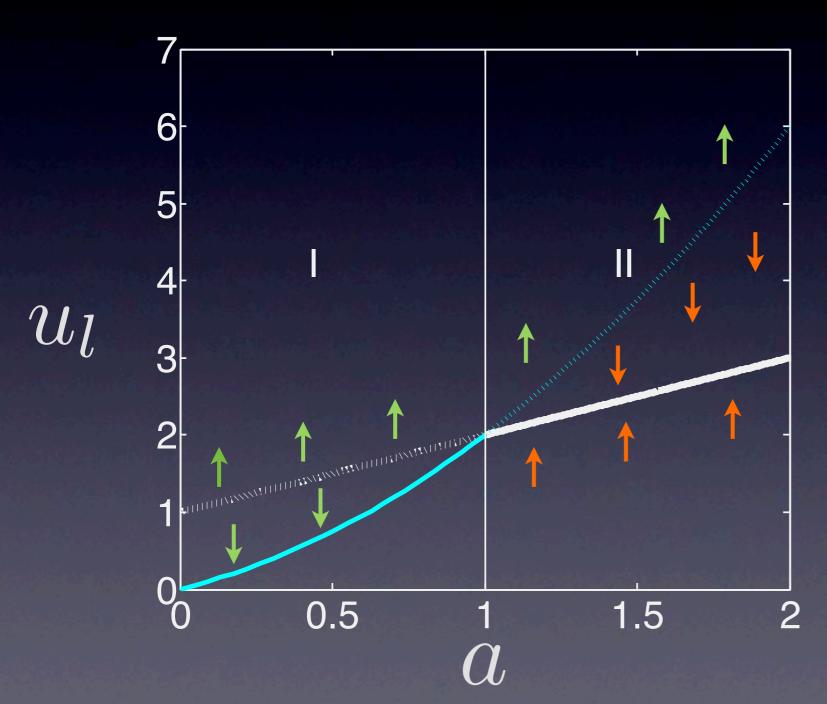
Conclusion

- The LPA really does recapitulate
 - I. Well mixed analysis results
 - 2. AND Turing analysis results

LP Diagram Interpretation

- The LPA does not directly predict the long term evolution of patterns.
- BUT, it can help infer the structure of a pattern.

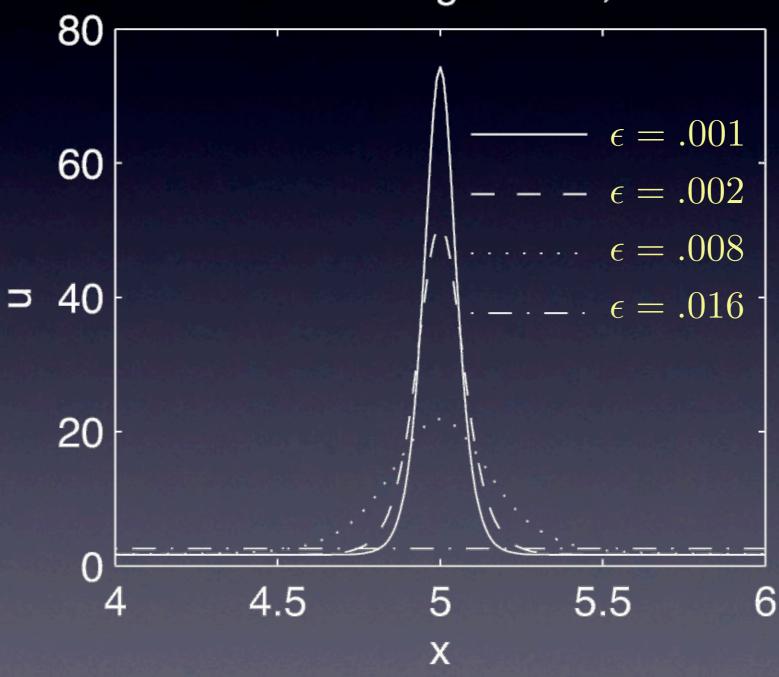
Schnakenberg LPA



- Consider region II.
- Sufficiently large perturbations grow to infinity.
- Diffusion mitigates growth and produces spikes.

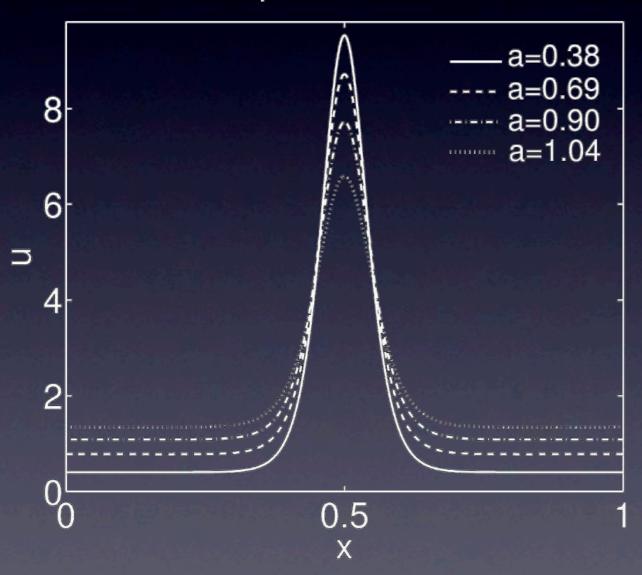
Spike Height Dependence





Turing vs Excitable

Spatial Profile



 The pattern resulting in the Turing and excitable regimes is the same!

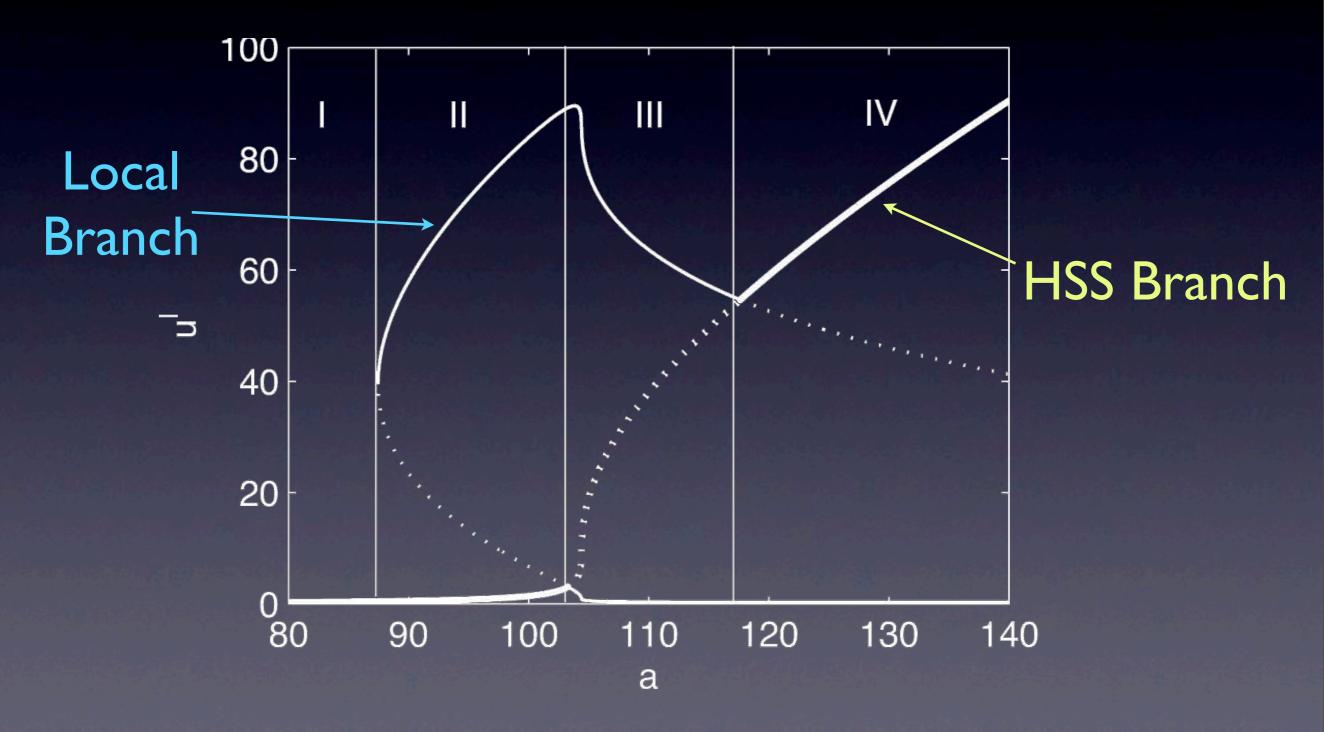
Substrate Inhibition

$$u_t(x,t) = a - u - \frac{\rho uv}{1 + u + Ku^2} + \epsilon \Delta u,$$

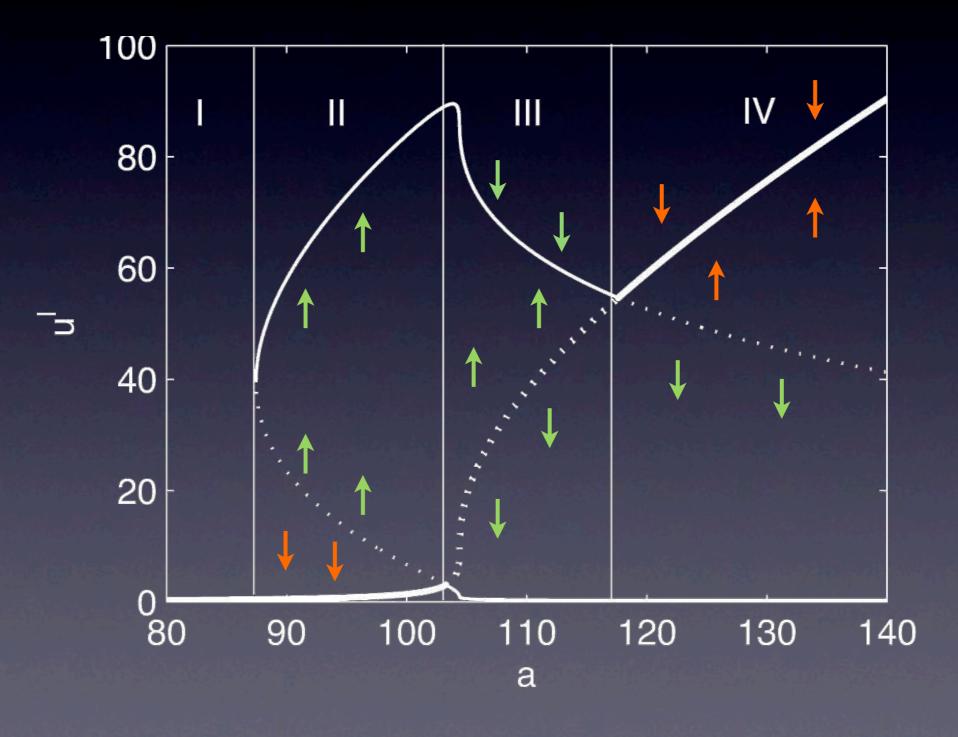
$$v_t(x,t) = \alpha(b-v) - \frac{\rho uv}{1 + u + Ku^2} + D\Delta v$$

- 'u' and 'v' are co-substrates that consume each other in a enzymatic reaction.
- Nonlinearity indicative of 'u' binding to enzyme and rendering it inert.

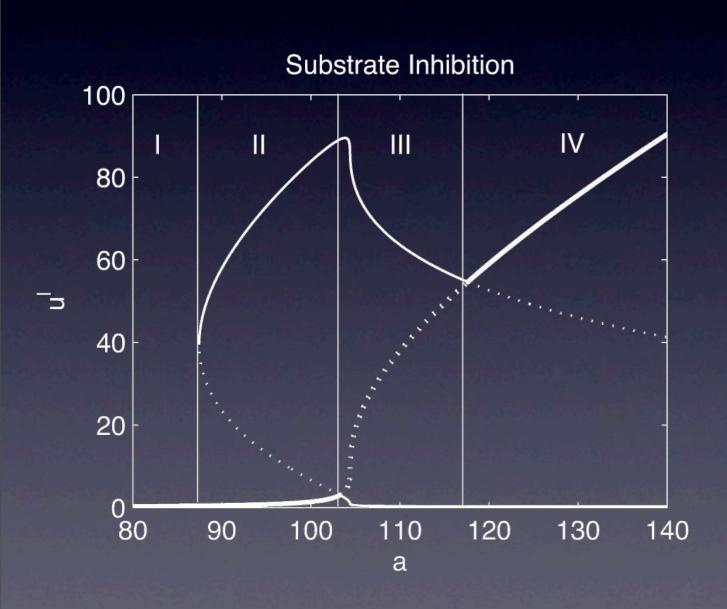
Substrate Inhibition LPA



Substrate Inhibition LPA



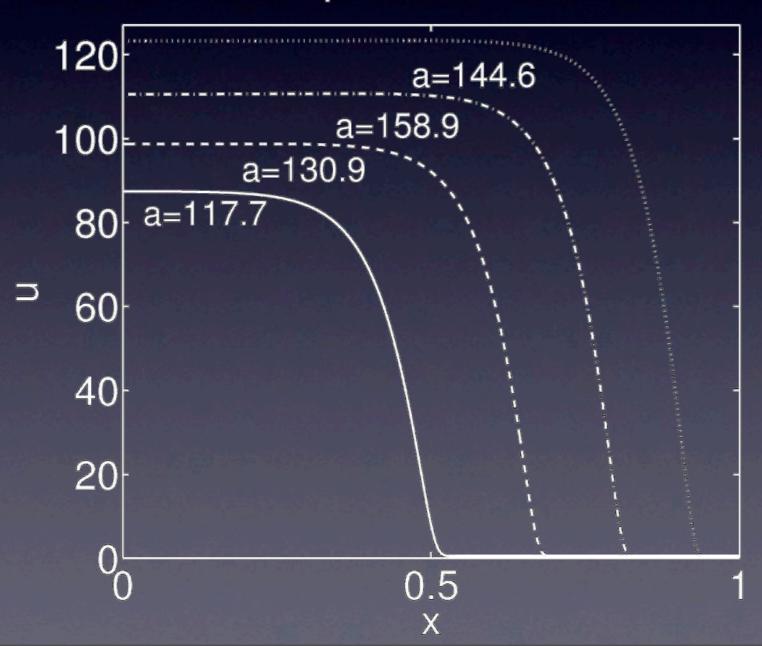
Substrate Inhibition LPA



- Region I No patterning.
- Region II Excitable
- Region III Turing
- Region IV Excitable

Turing vs Excitable

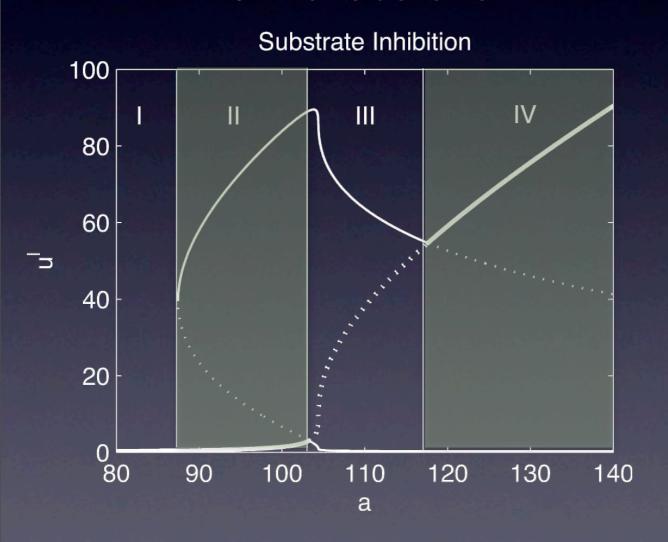
Spatial Profiles



 Again, excitable and Turing generated patterns have the same character.

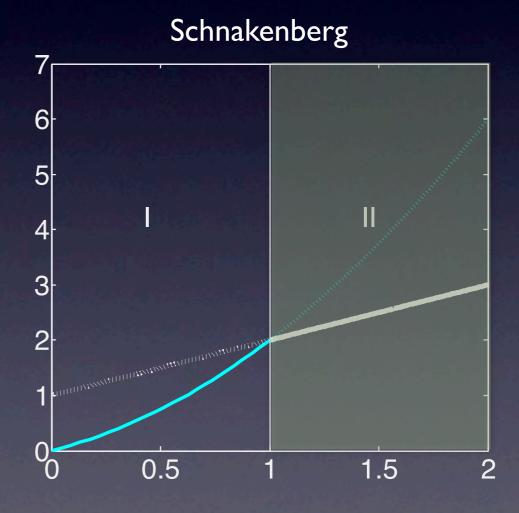
Types of excitable patterning.

 δ - bistable



• Interface Solutions

 δ - unstable



Spike Solutions

LP Eigenvalue

$$J_{LP} = \begin{bmatrix} f_u(u^g, v^g) & f_v(u^g, v^g) & 0\\ g_u(u^g, v^g) & g_v(u^g, v^g) & 0\\ 0 & f_v(u^l, v^g) & f_u(u^l, v^g) \end{bmatrix}$$

• The LP eigenvalue that determines stability can be interpreted as a Turing growth rate / eigenvalue.