

# Crime Modeling with Lévy Flights

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8/8/2012

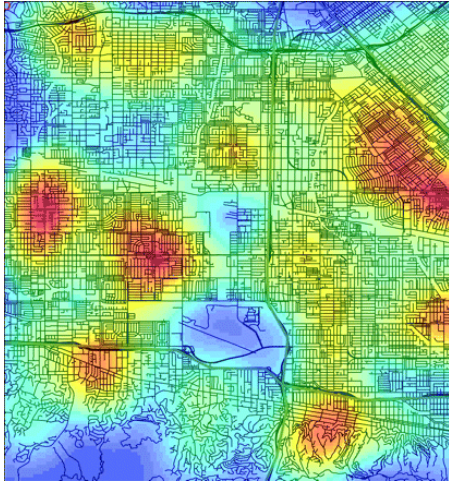


Figure: Crime Hot-Spot Pattern, Long Beach, LA. Short et al. 2010 [2]

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  - Considerable empirical evidence behind them.
- We focus on burglaries for simplicity.

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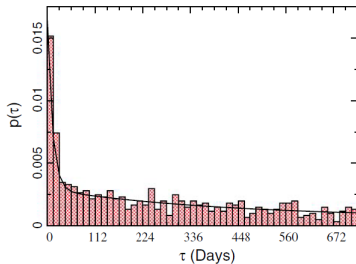


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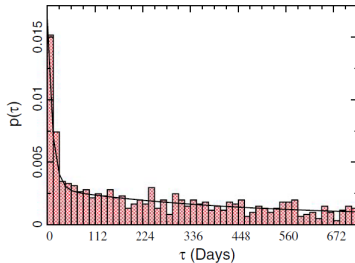


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- Broken Windows Theory: crime causes sense of lawlessness.

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- Starts with discrete model
  - Criminals are agents on a lattice that has “attractiveness” field
  - Every time step, criminals move to neighboring lattice spaces based on attractiveness.
  - Then decide to burgle or not based off attractiveness.
  - Crimes are self-exciting; cause attractiveness at lattice point and neighbors to increase.

## The Short et al Model (2008) (cont.)

Then, taking limits as grid spacing and time steps go to zero, we get system of PDEs

### The Model

$$A_t = \eta \Delta A - A + \rho A + A_0 \quad (1a)$$

$$\rho_t = \left( A \Delta \left( \frac{\rho}{A} \right) - \frac{\rho}{A} \Delta A \right) - \rho A + \bar{A} - A_0 \quad (1b)$$

$A$  = attractiveness at a point

$\rho$  = criminal density at a location

$A_0$  = a constant, background level of attractiveness

$\bar{A}$  = the spatially homogeneous equilibrium solution for  $A$ .

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- We use Lévy Flights
  - Power law distribution of step sizes  
( $P(k) \sim k^{-(2s+1)}, 0 < s \leq 1$ )
  - Fractal-like motion; reflects many scales of human movement.

## Implementation: Discrete

- We change the transition probability as follows:

$$p_{i \rightarrow i+1}(t) = \frac{A_{i+1}(t)}{A_{i+1}(t) + A_{i-1}(t)} \quad (\text{Brownian})$$

$$p_{i \rightarrow j}(t) = \frac{A_j(t)|i-j|^{-(2s+1)}}{\sum_{k \in \mathbb{Z}, k \neq i} A_k(t)|i-k|^{-(2s+1)}} \quad (\text{Lévy})$$

## Implementation: Continuous

- From before we had:

$$A_t = \eta \Delta A - A + \rho A + A_0,$$

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- Using our new transition probabilities and taking limits as before we get:

$$A_t = \eta \Delta A - A + \rho A + A_0 \quad (\text{No change})$$

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where

$$\Delta^s A = c_s \int_{-\infty}^{\infty} \frac{A(y) - A(x)}{|y - x|^{2s+1}} dy, \quad (2)$$

$c_s$  is a constant and  $0 < s \leq 1$ .

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  - Is a non-local operator. Leads to super-diffusion. Degree of non-locality controlled by  $s$ .
  - Fourier Transform has nice property:  $\mathcal{F}_{x \rightarrow q}\{\Delta^s A\} = -|q|^{2s} \hat{A}$

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- Then use MATLAB's stiff ODE solver.
- We used to use a forward Euler spectral method, but that could not handle much of the parameter space.



# Examples

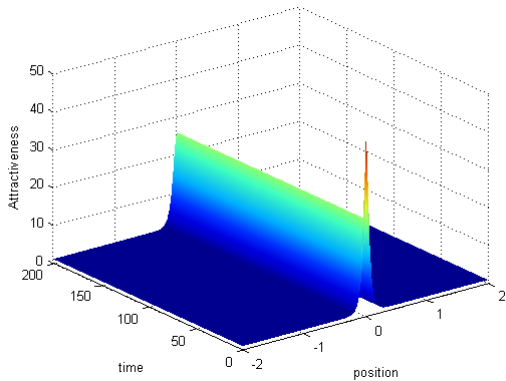


Figure: Single Hot-Spot.

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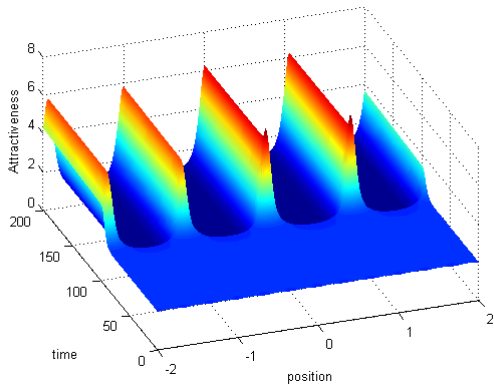


Figure: Four Hot-Spots,  $D = 1$ ,  $s = 1$ ,  $\varepsilon = 0.05$ .

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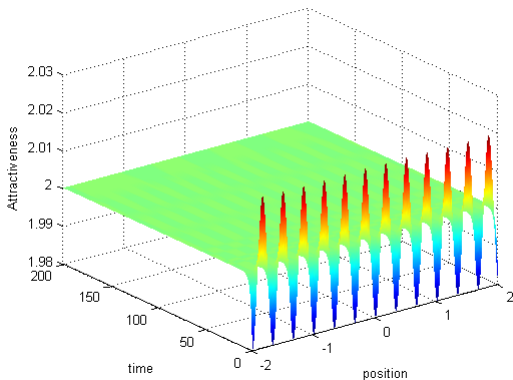


Figure: No Hot-Spot,  $D = 1, s = 0.5, \varepsilon = 0.05$ .

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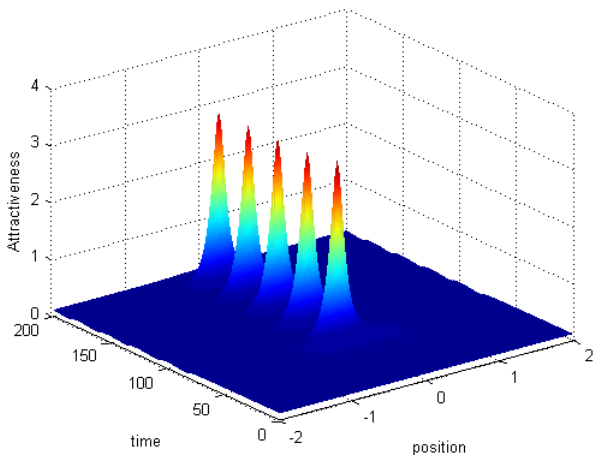


Figure: Oscillating Hot-Spots,  $s = 0.7, \eta = 0.1, \bar{\rho} = 0.4, \bar{A} = 0.12$ .

## Linear Stability of Homogeneous Equilibrium

- The homogeneous equilibrium does not change from Short et al. We get

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- Perturb from the homogeneous equilibrium as follows and plug into linearized equations:

$$A(x, t) = \bar{A} + \delta_A e^{\sigma t} e^{ik \cdot x}, \quad (4a)$$

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- Solving the resulting eigenvalue problem results in this condition for instability: there *exists*  $|k|$  such that

$$\eta |k|^{2s+2} - |k|^{2s} (3\bar{\rho} - 1) + \eta \bar{A} |k|^2 + \bar{A} < 0. \quad (5)$$

## Stability (cont.)

The first attempt to solve Eq. (5): the condition for instability is equivalent to, there **exists**  $|k|$  such that

$$\bar{\rho} > \frac{1}{3} (1 + \eta|k|^2) \left( 1 + \frac{\bar{A}}{|k|^{2s}} \right). \quad (6)$$



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where  $|k_*|$  is a root of

$$|k|^{2s+2} + \bar{A}(1 - s)|k|^2 - \frac{\bar{A}s}{\eta} = 0. \quad (7)$$

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The **second** attempt to solve Eq. (5): the condition for instability is equivalent to, there **exists**  $|k|$  such that

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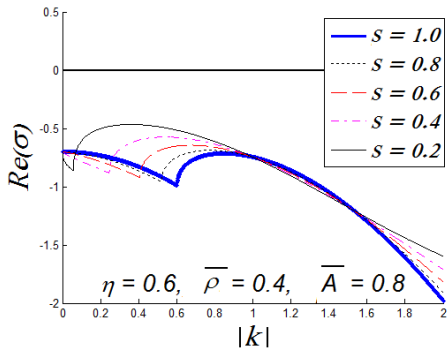
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- Has bifurcations in  $s$ , so changing degree of Lévy Flight alters stability.

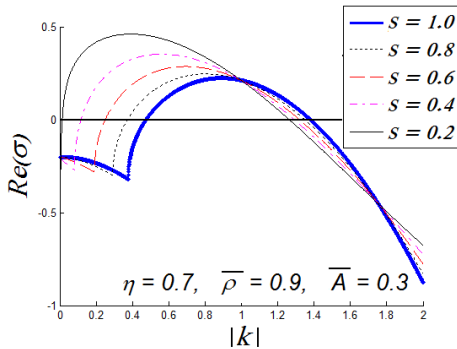
# Changing Stability with Varying Parameter



(a) A stable regime

Figure: Different possibilities of the effect of fractional diffusion.

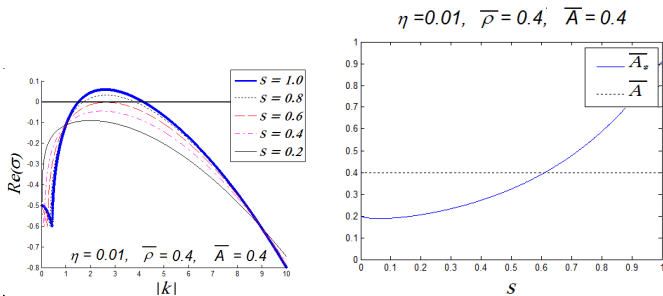
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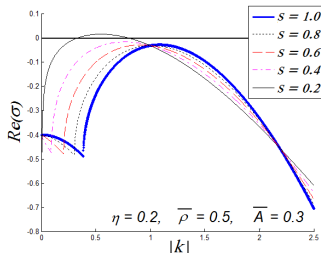


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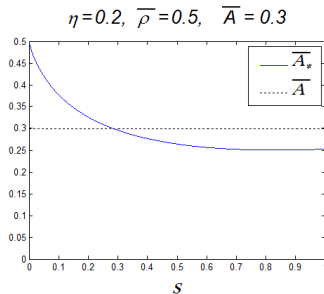
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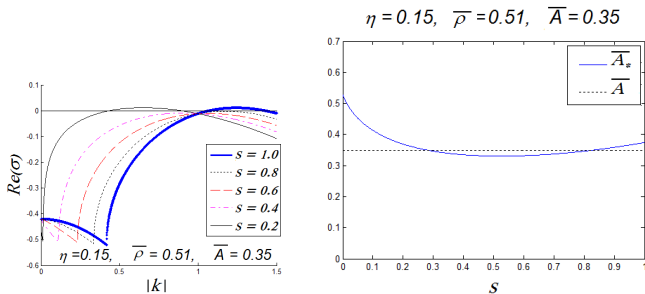
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(a) Fractional diffusion leads to stability and then instability  
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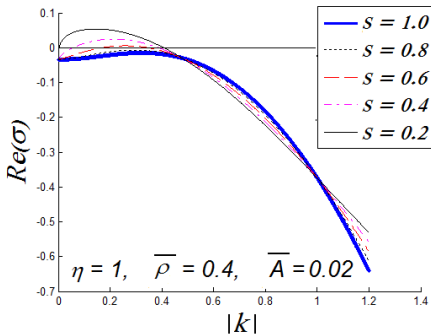
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## Changing Stability with Varying Parameter

*Remark.* The fixed points  $|k|$  of  $\sigma(|k|)$  with respect  $s$  are given by

$$|k_1| = 1, \quad |k_2| = \sqrt{\frac{6(\bar{\rho} - \frac{1}{3}) + 3\bar{A}}{2\eta}}. \quad (12)$$

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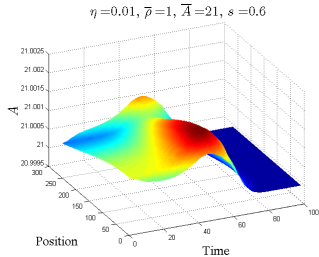
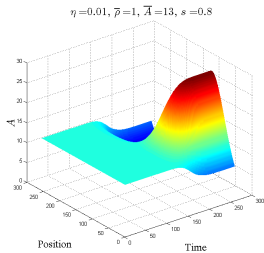
(a) A regime in which  $|k_2| < |k_1| = 1$

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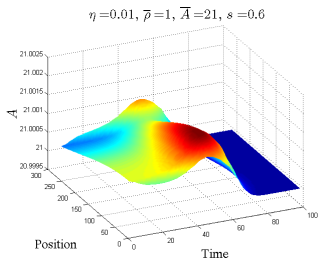
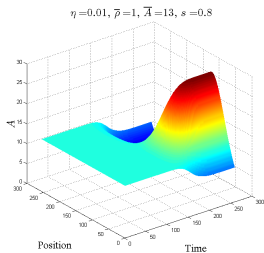
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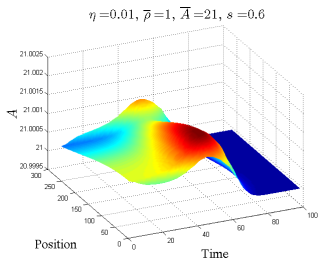
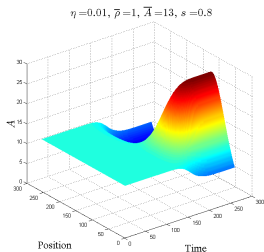
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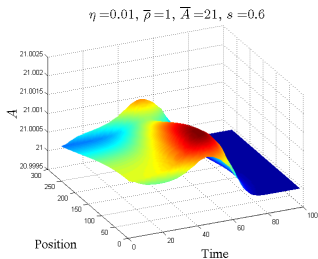
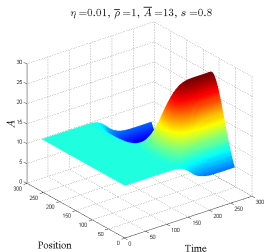
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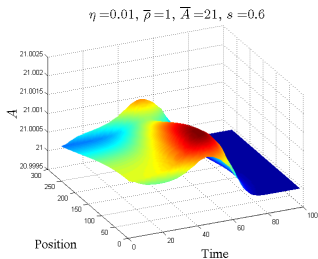
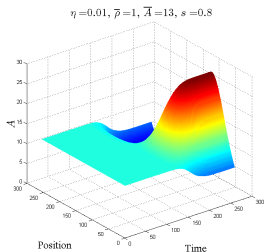
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- The variance and its derivative.
- The difference of the maximum of the solution in the final frame from  $\bar{A}$  as a percentage of  $\bar{A}$ .
- The difference between the maximum and the minimum.
- An ensemble method.

# Numerical Verification (cont.)

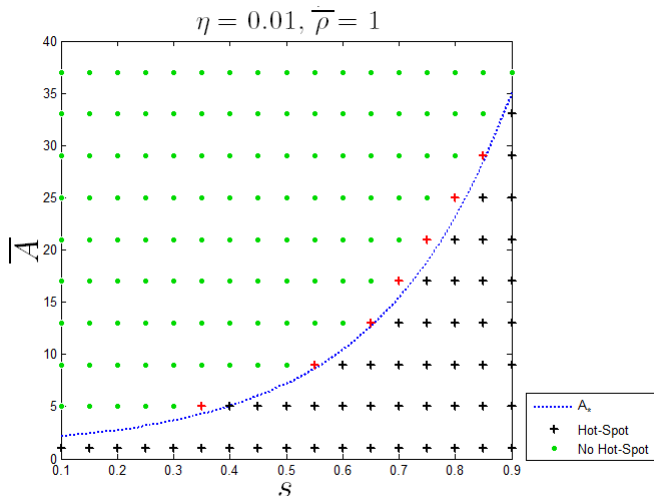


Figure: A parameter analysis with a bifurcation curve. Fix  $\bar{\rho}$  and  $\eta$ .

# Numerical Verification (cont.)

$$\eta = 0.01, \bar{\rho} = 1, \bar{A} = 13, s = 0.8$$

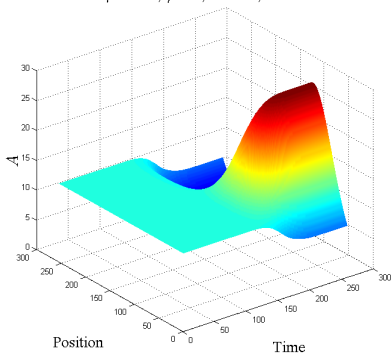


Figure: A hot-spot formation when  $\bar{A} = 13$ ,  $s = 0.8$ .

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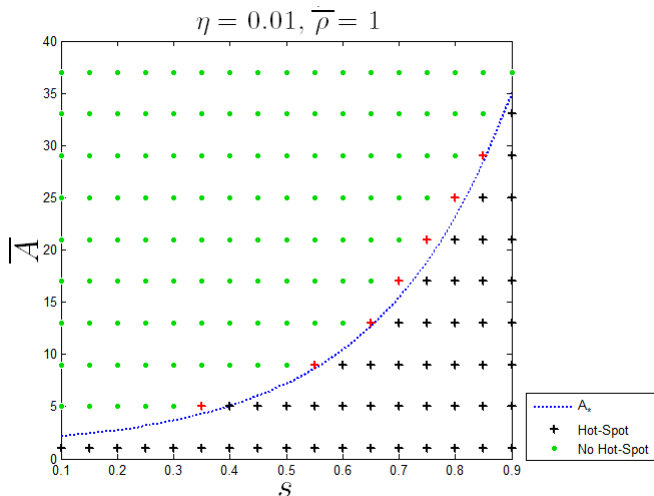


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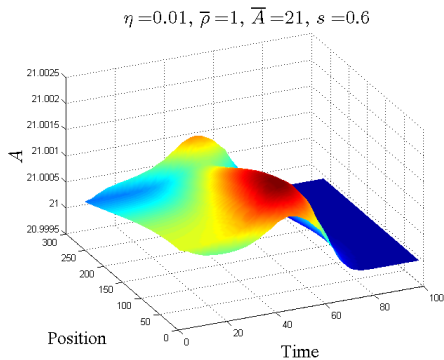
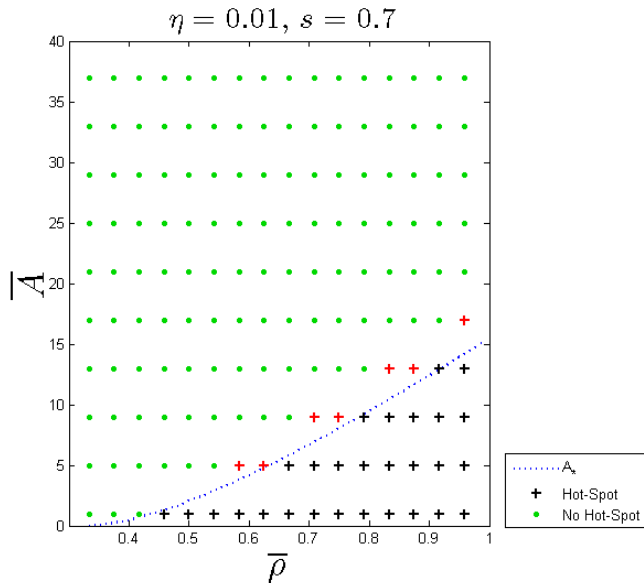


Figure: No hot-spot formation when  $\bar{A} = 21, s = 0.6$

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- Are the hotspots any different under the two regimes?
- Yes and no. Attractiveness hotspots do not change, and first order approximations from Kolokolnikov et al. still work very well.
- But distribution of criminals changes.

## Hotspot Shape (cont.)

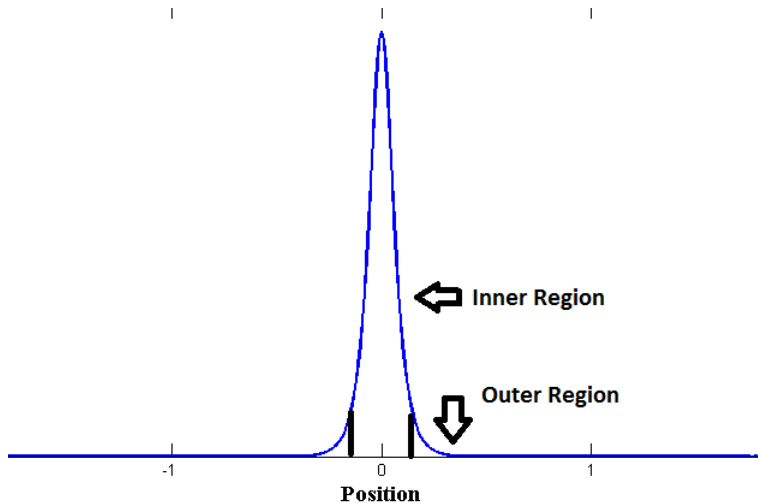


Figure: The inner region and the outer region of a hotspot.

## Hotspot Shape (cont.)

- Let  $x = \varepsilon y$ , and  $v = \rho/A^2$ .

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- Let  $x = \varepsilon y$ , and  $v = \rho/A^2$ .
- In the inner region ( $|x| < \varepsilon$ ),

$$A \sim \varepsilon^{-1} v_0^{-1/2} w(y), \quad (12)$$

$$v \sim v_0, \quad (13)$$

where  $v_0$  and  $v_1$  are constants, and  $w = \sqrt{2} \operatorname{sech} y$  (same as Kolokolnikov et al.).



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- In the outer region ( $\varepsilon \ll |x| \leq l$ ), we have

$$A = \alpha + o(1), \quad (14a)$$

$$v = h_0(x) + o(1), \quad (14b)$$

where

$$\Delta^s h_0(x) = \zeta = \frac{\alpha - \gamma}{D_0 \alpha^2} < 0, \quad 0 < |x| \leq l, \quad (h_0)_x(\pm l) = 0, \quad (15)$$

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# Acknowledgments

Thanks...

- Theodore Kolokolnikov
- Scott McCalla
- UCLA and REU Program Organizers



- Harvey Mudd College Mathematics Department for funding Tum



- Nestor Guillen for creating the Nonlocal Equations Wiki (<http://www.ma.utexas.edu/mediawiki>)



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