

Summer school, CIRM, Marseille 2016

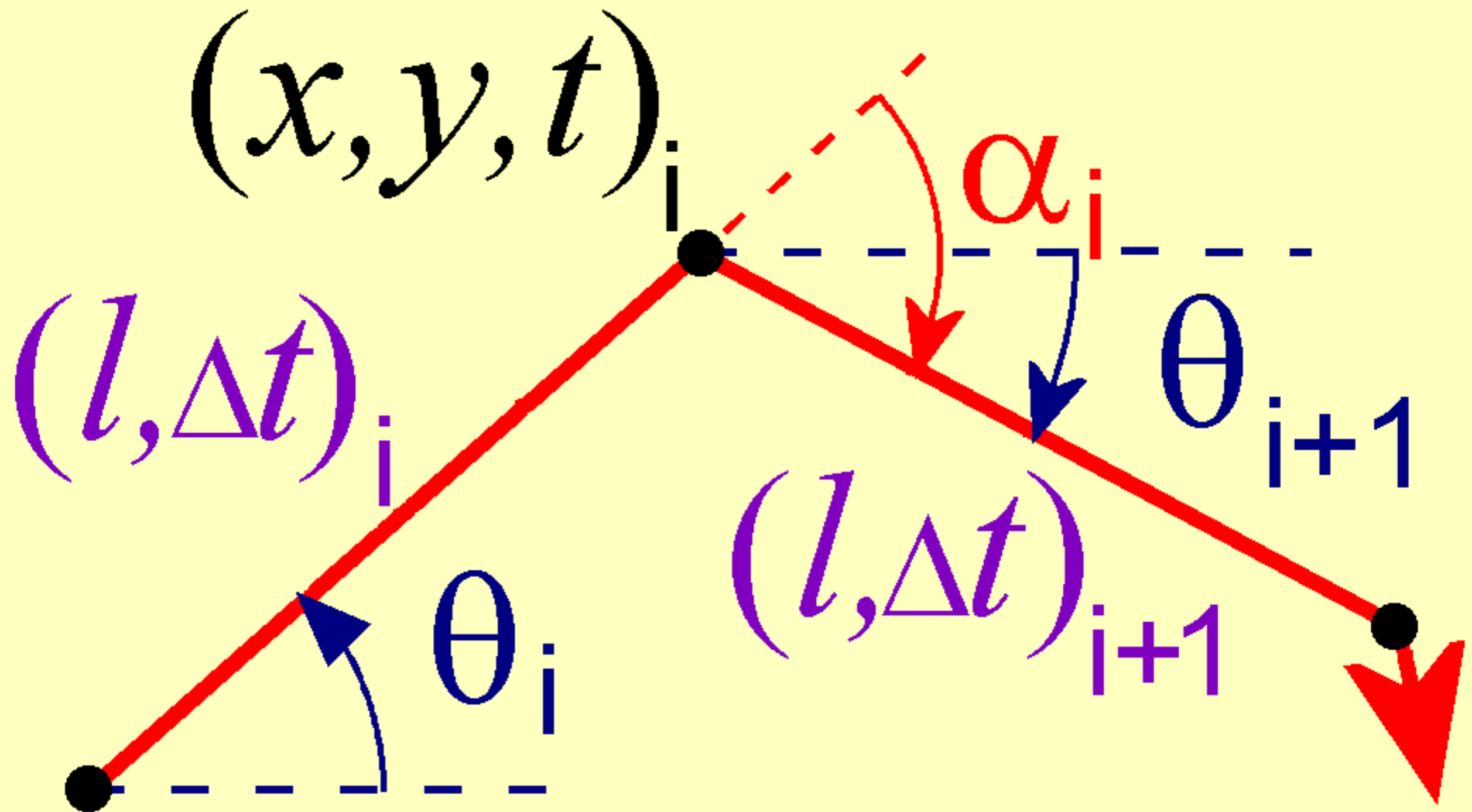
Animal movements at various scales

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NOODLES
MORNING
FEELING

Discrete movement representation ...



... and sampling issue.

Mean Squared Net Displacement (MSND)

$$R_n^2 = \left(\sum_{j=1}^n l_j \cos(\theta_j) \right)^2 + \left(\sum_{j=1}^n l_j \sin(\theta_j) \right)^2 = \sum_{j=1}^n l_j^2 + 2 \sum_{j=1}^{n-1} \sum_{k=j+1}^n l_j l_k \cos(\theta_k - \theta_j)$$

Assuming that step lengths l are not auto-correlated and not cross-correlated with directions θ , one gets:

$$E(R_n^2) = nE(l^2) + 2E(l)^2 \sum_{j=1}^{n-1} \sum_{k=j+1}^n E[\cos(\sum_{h=j}^{k-1} \alpha_h)] = nE(l^2) + 2E(l)^2 \sum_{m=1}^{n-1} (n-m)C_m$$

Example 1: Biased Random Walk (with goal at infinity)

$$\sum_{m=1}^{n-1} (n-m)c_m = n(n-1)c/2$$

Example 2: Systematic square walk

$$\sum_{m=1}^{n-1} (n-m)c_m = \frac{1 - \sin[(n+1)90^\circ] - n}{2}$$

Example 3: Balanced Correlated Random Walk

$$\sum_{m=1}^{n-1} (n-m)c_m = \frac{c}{1-c} \left(n - \frac{1-c^n}{1-c} \right) \quad \begin{array}{l} \text{(Brownian motion: } c=0) \\ \text{(Long-term dispersal: } n \rightarrow \infty) \end{array}$$

Mean Squared Net Displacement (MSND)

Balanced Correlated Random Walk

$$E(R_n^2) = nE(l^2) + E(l)^2 \frac{2c}{1-c} \left(n - \frac{1-c^n}{1-c} \right)$$

$$E(R_n^2)_a = L_n E(l) \left(\frac{1+c}{1-c} + b^2 \right) = 4Dt$$

with path length $L_n = nE(l)$
and coefficient of variation of
step length b ($E(l^2) = E(l)^2(1+b^2)$)

Transport mean free path l^*

For a non-correlated RW (BM: $c=0$) with step length l^*

$$E(R_n^2) = L_n E(l^*) (1+b^2) \quad \Rightarrow \quad E(l^*) = \frac{1+c+b^2(1-c)}{(1+b^2)(1-c)} E(l)$$

Particular cases:

Constant step length ($b=0$) for both BM and CRW: $l^* = l(1+c)/(1-c)$

Exponential distribution ($b=1$) for both BM and CRW: $E(l^*) = E(l)/(1-c)$

How to compute the path tortuosity of random search movements?

Sinuosity index for CRW: **S**

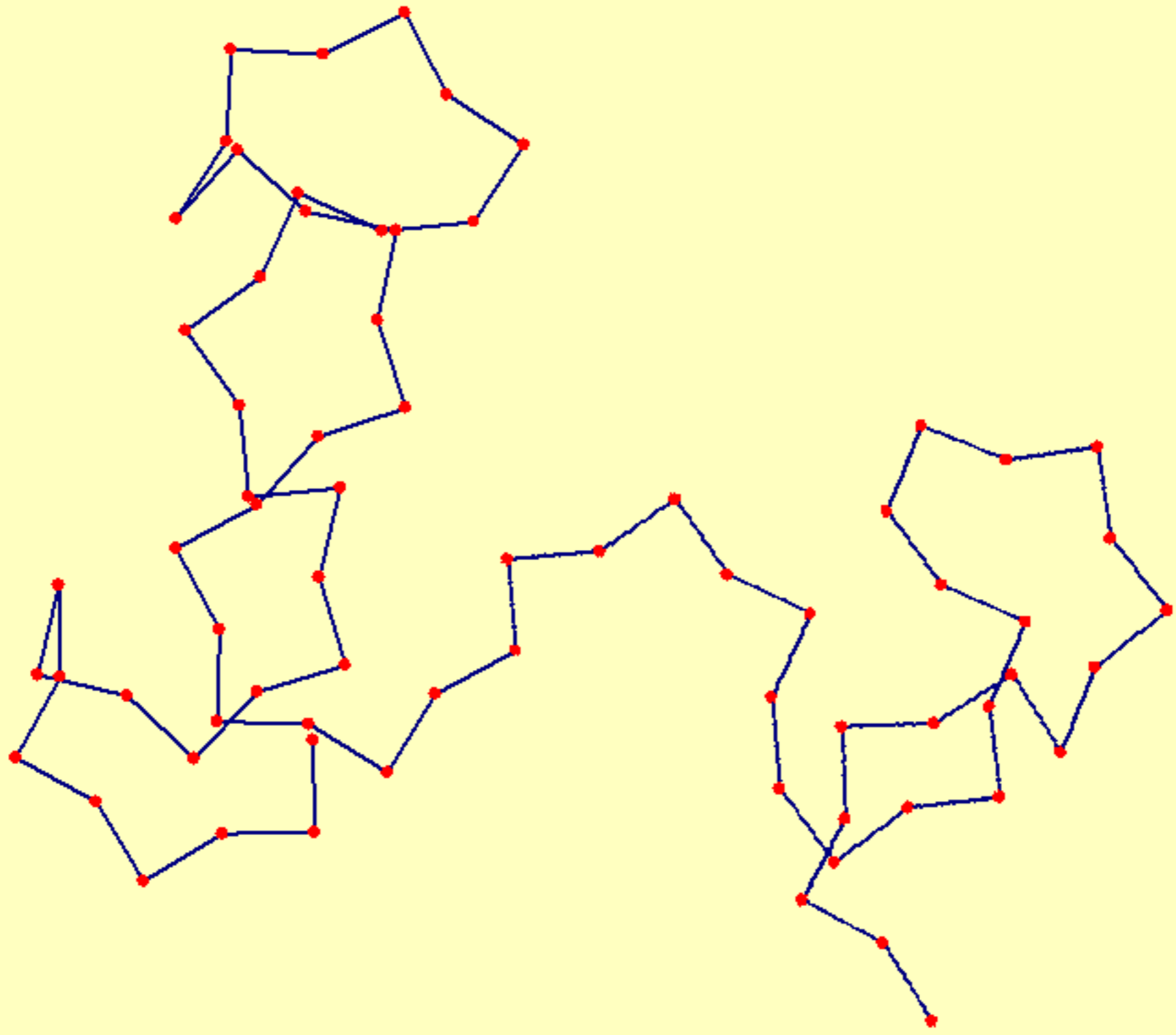
$$D = V/S^2 \quad \begin{array}{l} D: \text{coefficient of diffusion} \\ t: \text{time, } V: \text{mean speed} \end{array}$$

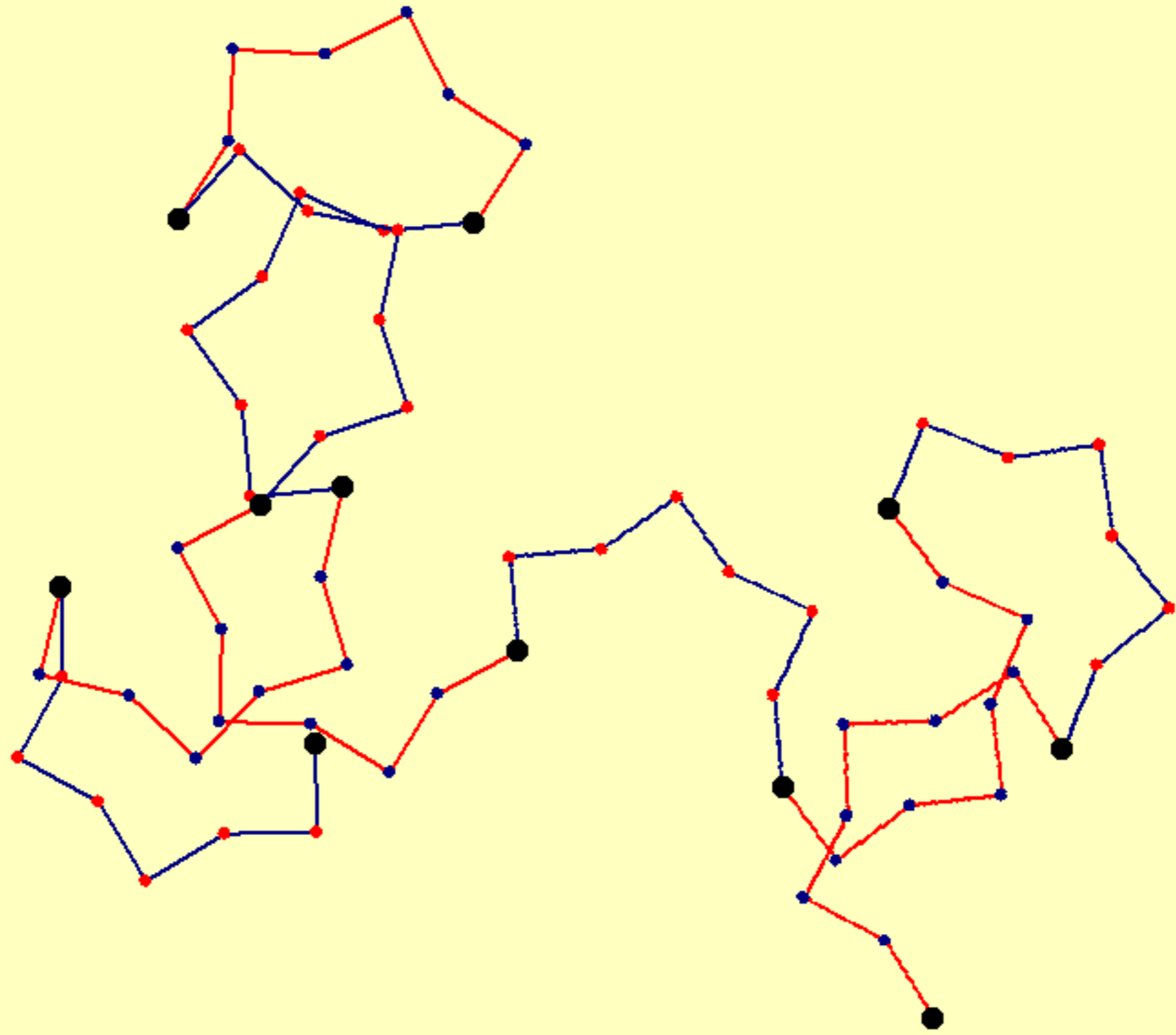
$$E(R_n^2)_a = L_n E(l) \left(\frac{1 - c^2 - s^2}{(1 - c)^2 + s^2} + b^2 \right) = 4Dt$$

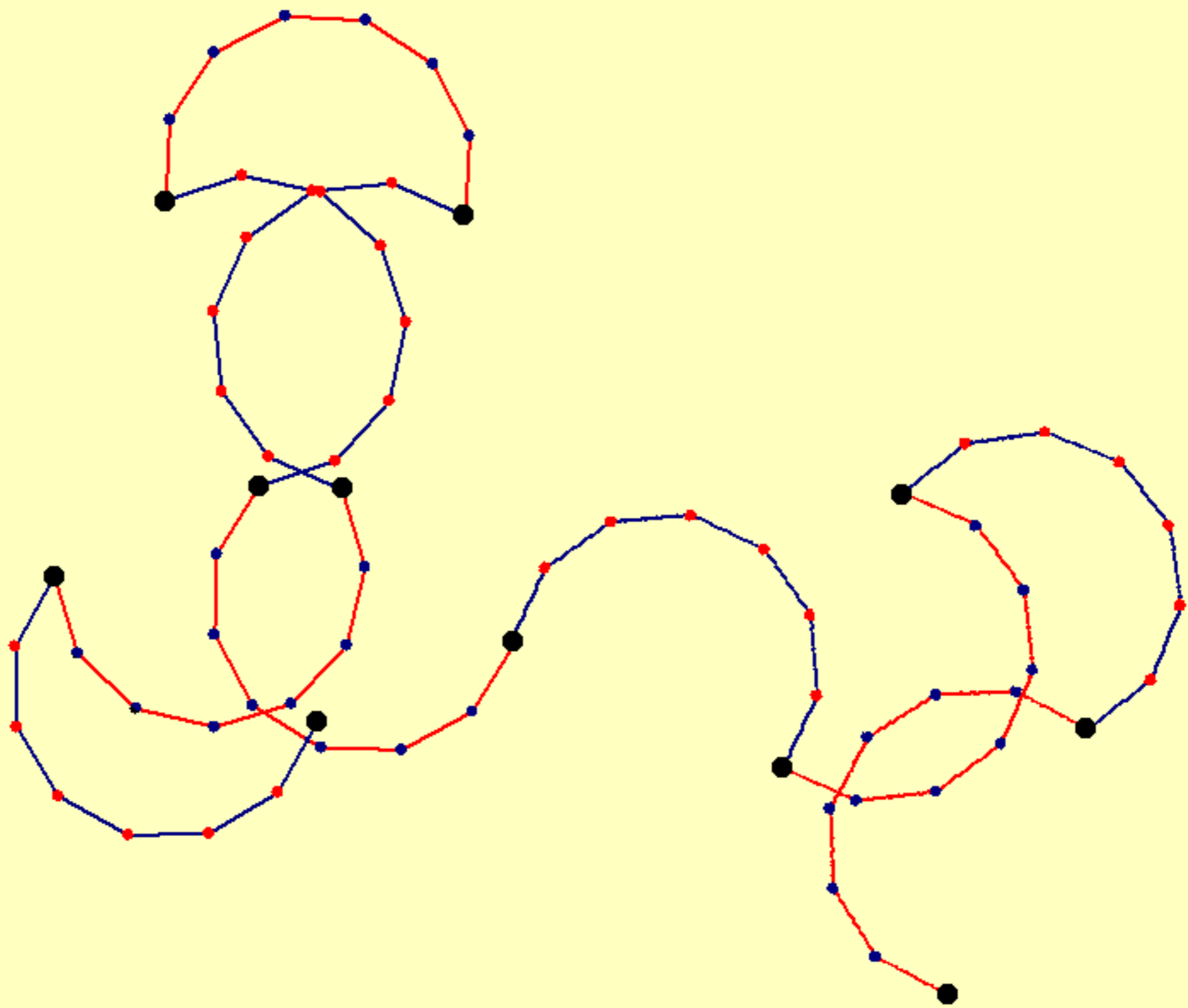
Balanced CRW:

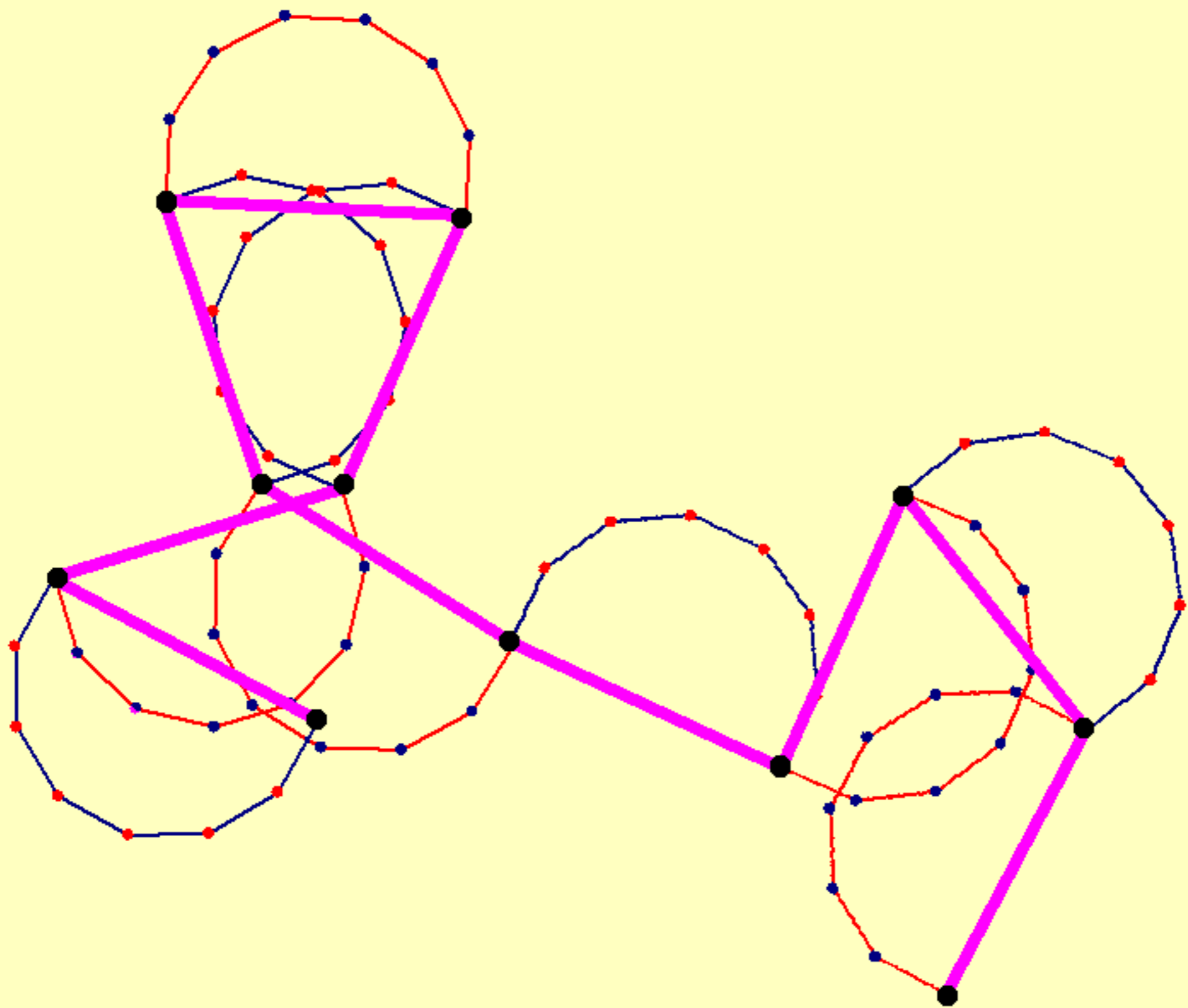
Modelling
$$S = 2 \left[E(l) \left(\frac{1+c}{1-c} + b^2 \right) \right]^{-0.5} \simeq \sigma(\alpha) / \sqrt{E(l)} \quad \text{for } c > 0.5$$

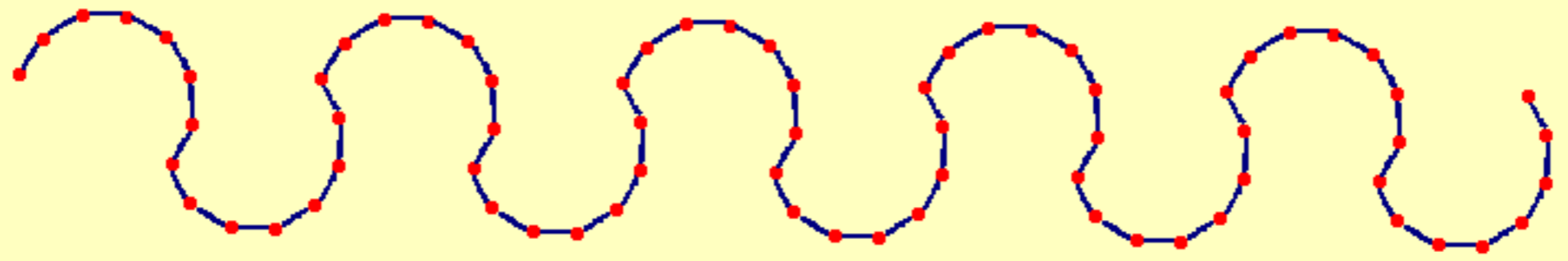
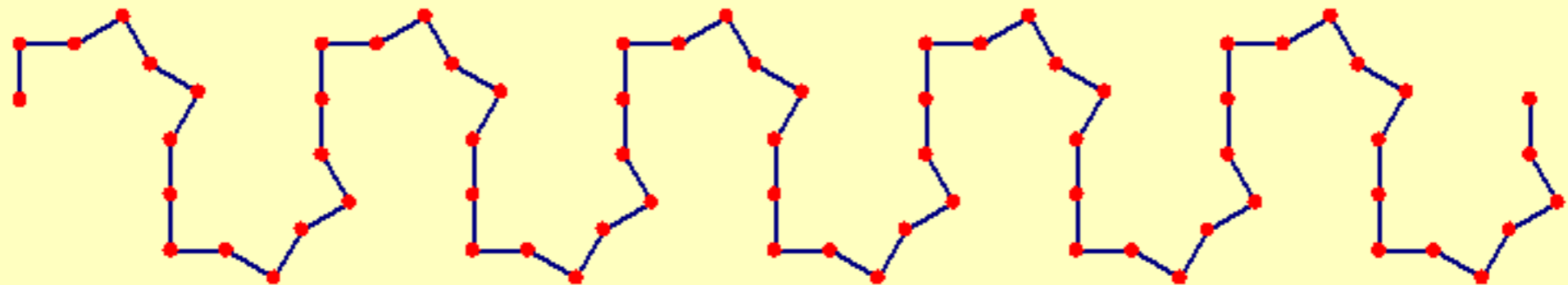
Analysis
$$S = \left[\frac{2}{l_r} \tan \left(\frac{\pi}{2} (1 - c_r) \right) \right]^{0.5} \simeq 1.18 \sigma(\alpha_r) / \sqrt{l_r} \quad \text{for } c > 0.5$$

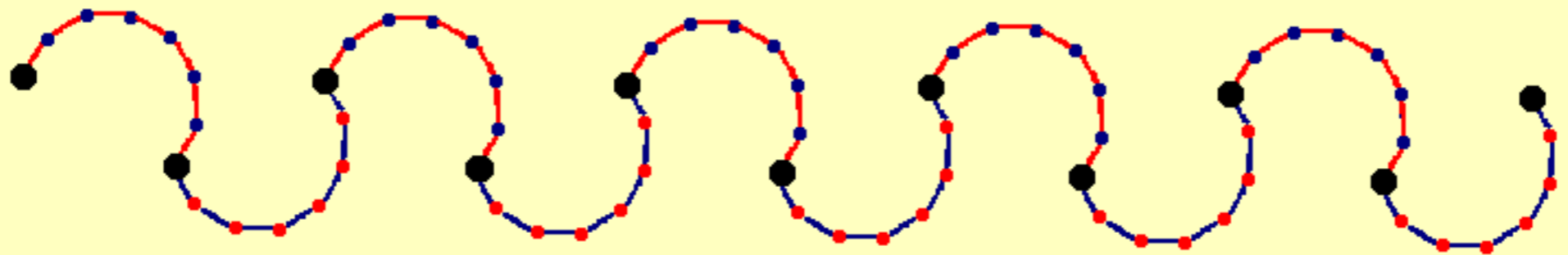
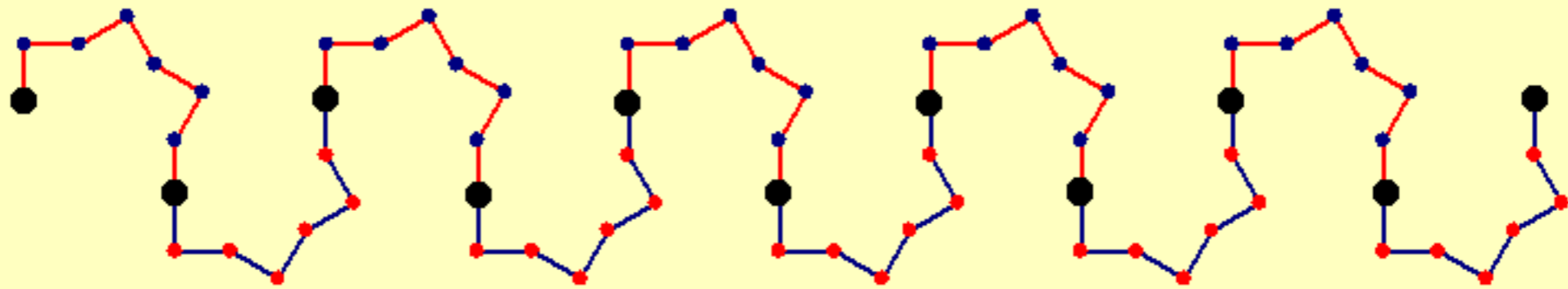


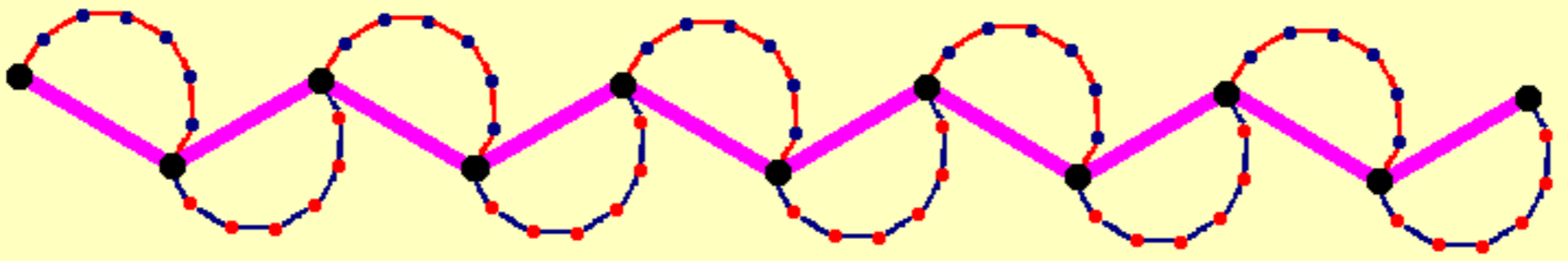
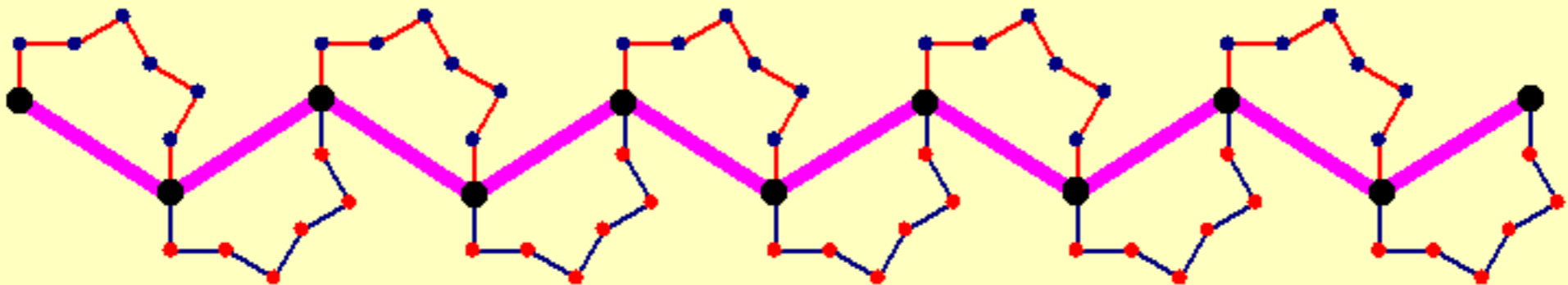








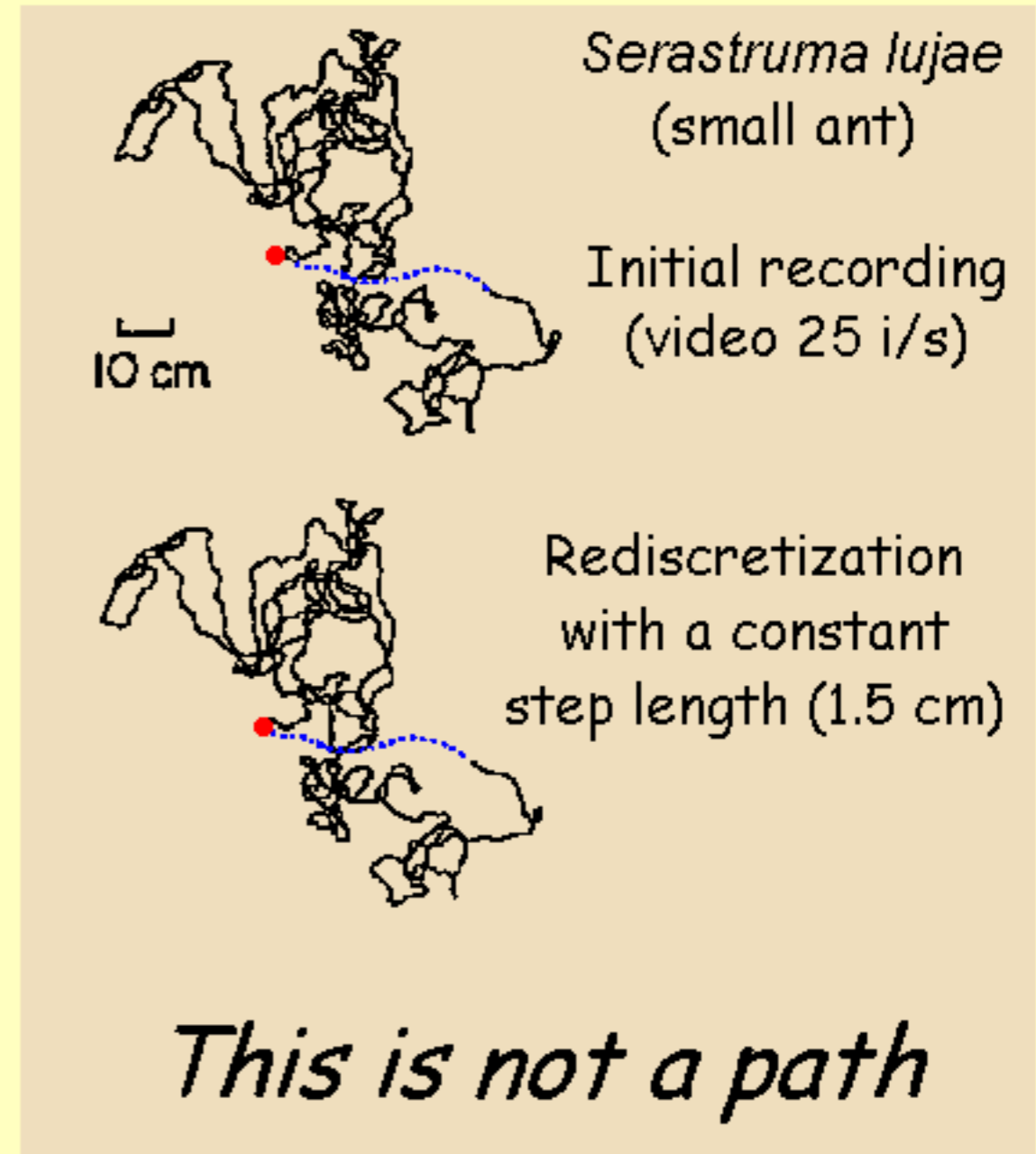




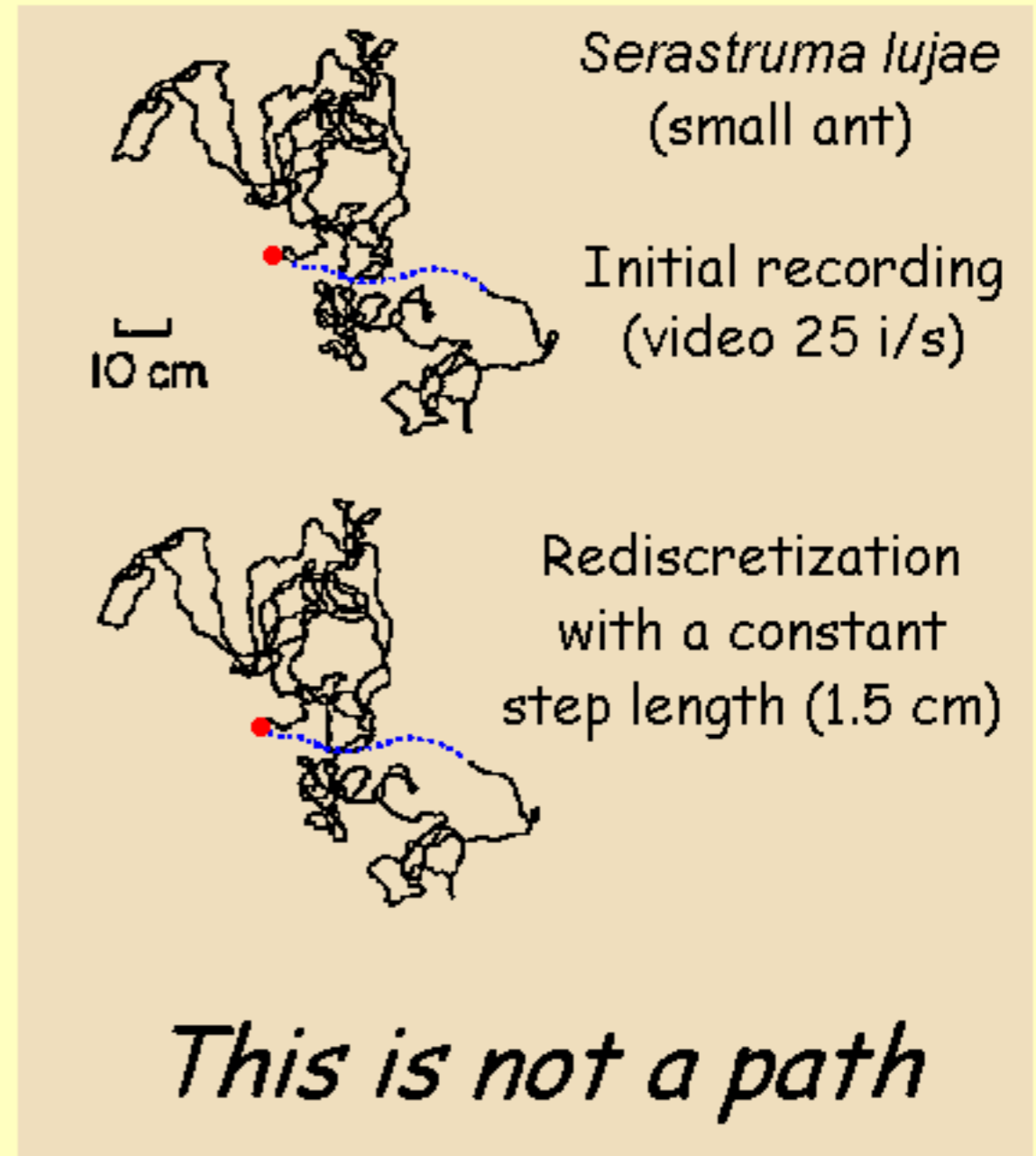
Real World vs. World Models



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Real World vs. World Models



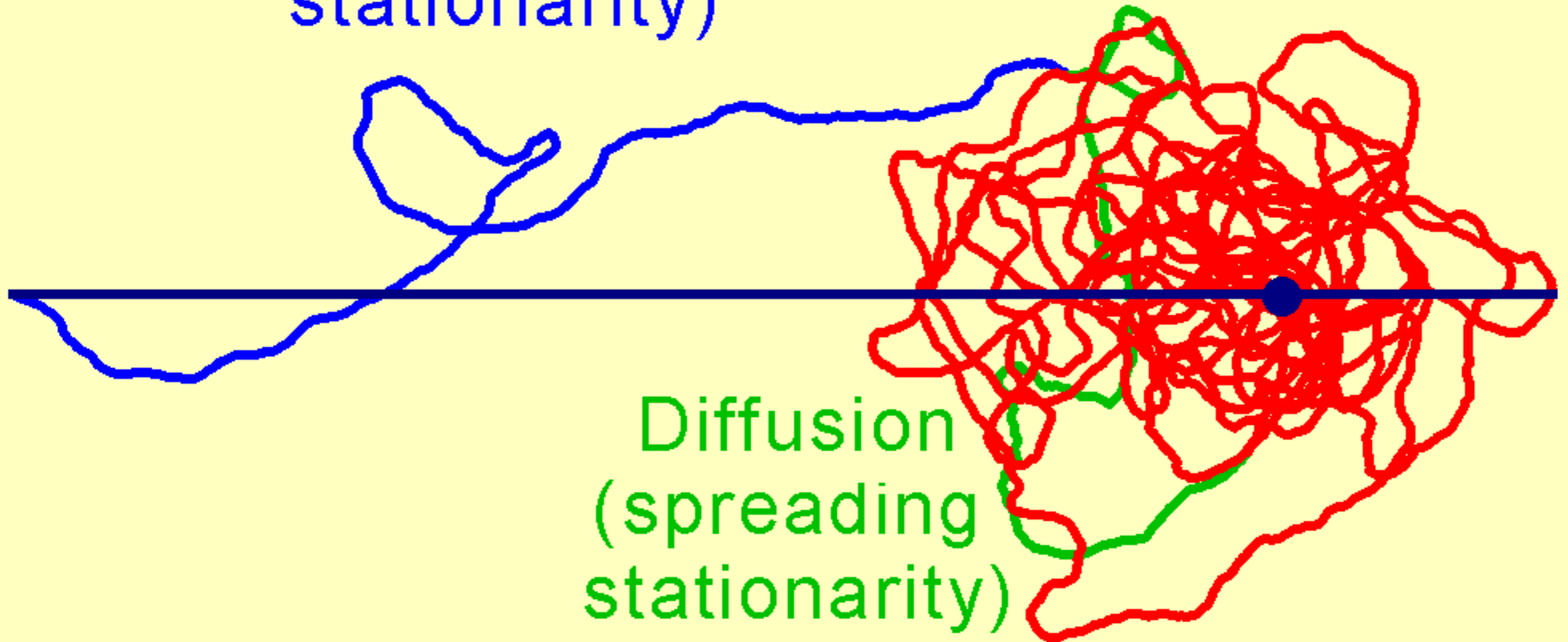
Movement Process => Pattern (path) => Path representation

inference

Various patterns generated by ... a single process

Advection
(direction
stationarity)

Search-loops
(location
stationarity)



Diffusion
(spreading
stationarity)

Similar patterns generated by ... quite different processes

Lévy Walk
(scale-free, single mode)

$$p(\theta) = (2\pi)^{-1}$$
$$p(L) = (\mu-1)L_{min}^{\mu-1} L^{-\mu}$$
$$1 < \mu = 2 < 3$$

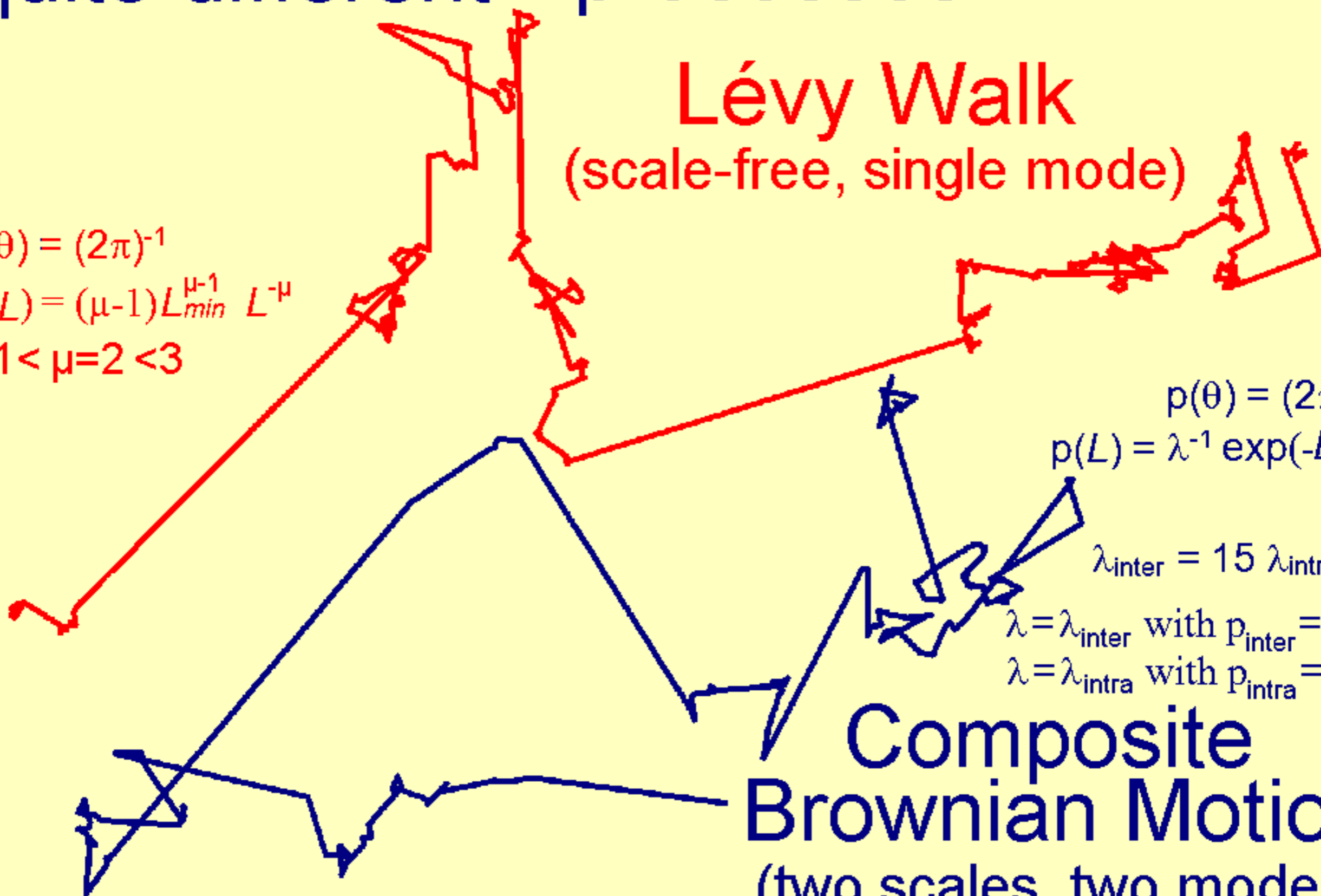
$$p(\theta) = (2\pi)^{-1}$$
$$p(L) = \lambda^{-1} \exp(-L/\lambda)$$

$$\lambda_{inter} = 15 \lambda_{intra}$$

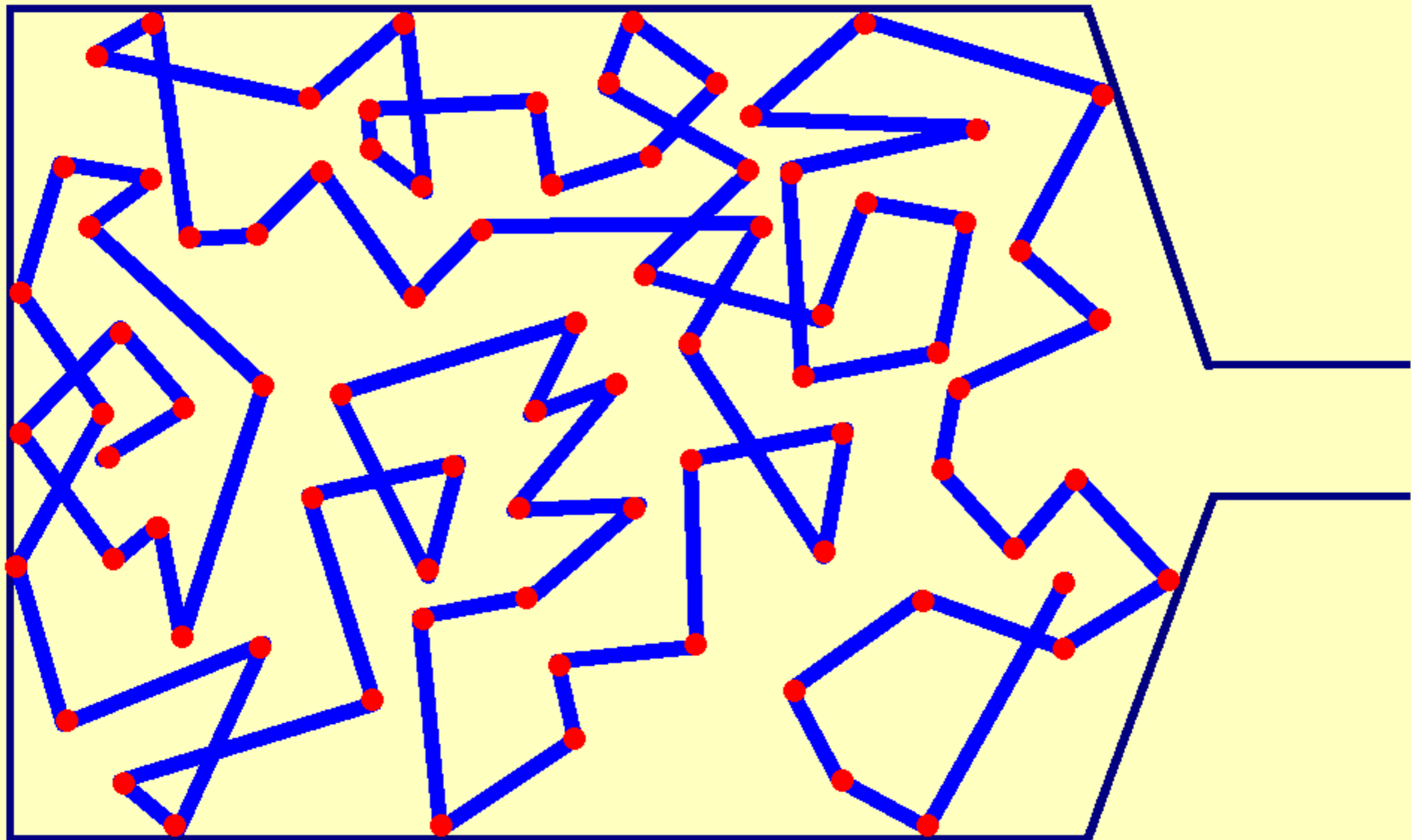
$$\lambda = \lambda_{inter} \text{ with } p_{inter} = 0.1$$

$$\lambda = \lambda_{intra} \text{ with } p_{intra} = 0.9$$

**Composite
Brownian Motion**
(two scales, two modes)



Consider a gas molecule in a bottle
How many movement scales?



EVIDENCE FOR SPATIAL SCALE-SPECIFIC MOVEMENT PROCESSES

NAVIGATION BEHAVIOUR

Because of a trade-off between working range and accuracy, several (usually three) scales can be distinguished:

- + small scale: pinpointing the goal location
- + medium scale: navigating through a familiar environment
- + large scale: navigating through large unfamiliar environments

These scales are usually uncoupled and used sequentially

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FORAGING BEHAVIOUR

Because of the heterogeneity of the environment, at least two scales can be distinguished:

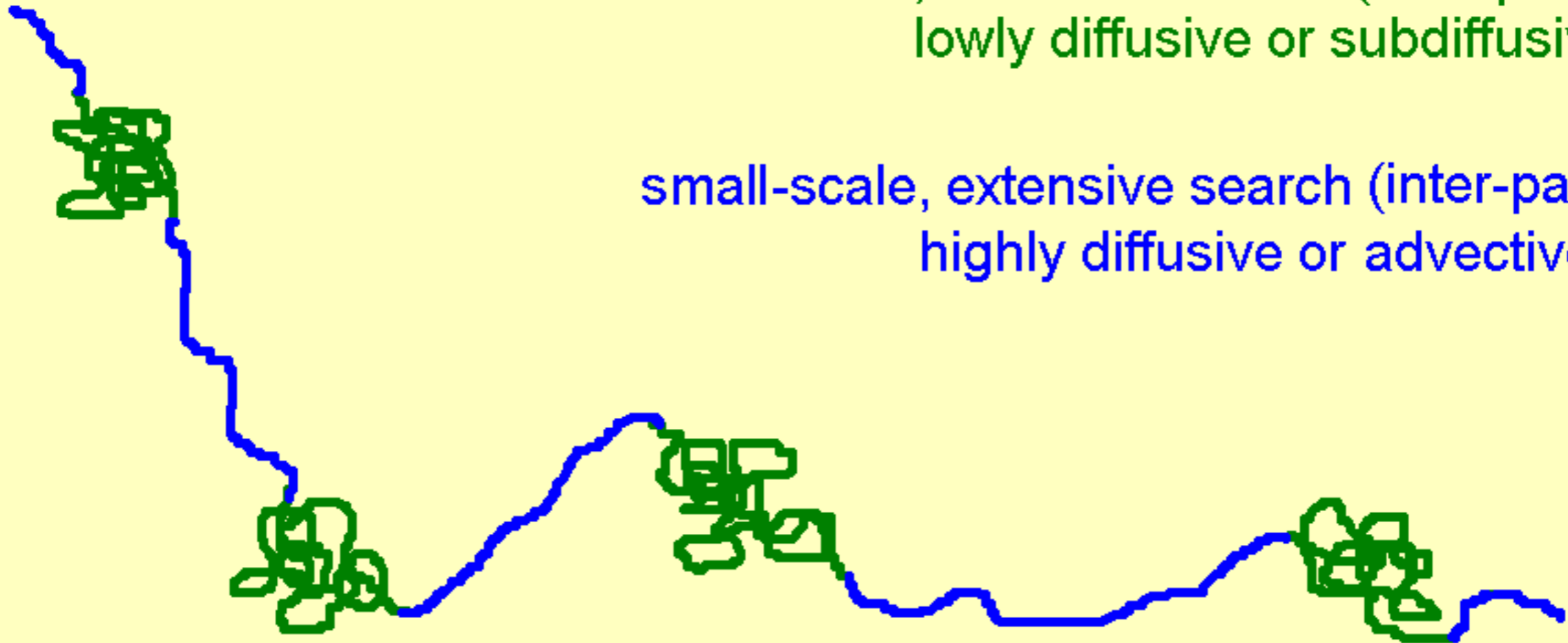
- + small scale: search for prey items between and within patches
- + large scale: patch to patch movement

These scales may be partly coupled and are used simultaneously

Sequential search modes and simultaneous spatial scales

small-scale, intensive search (intra-patch):
lowly diffusive or subdiffusive

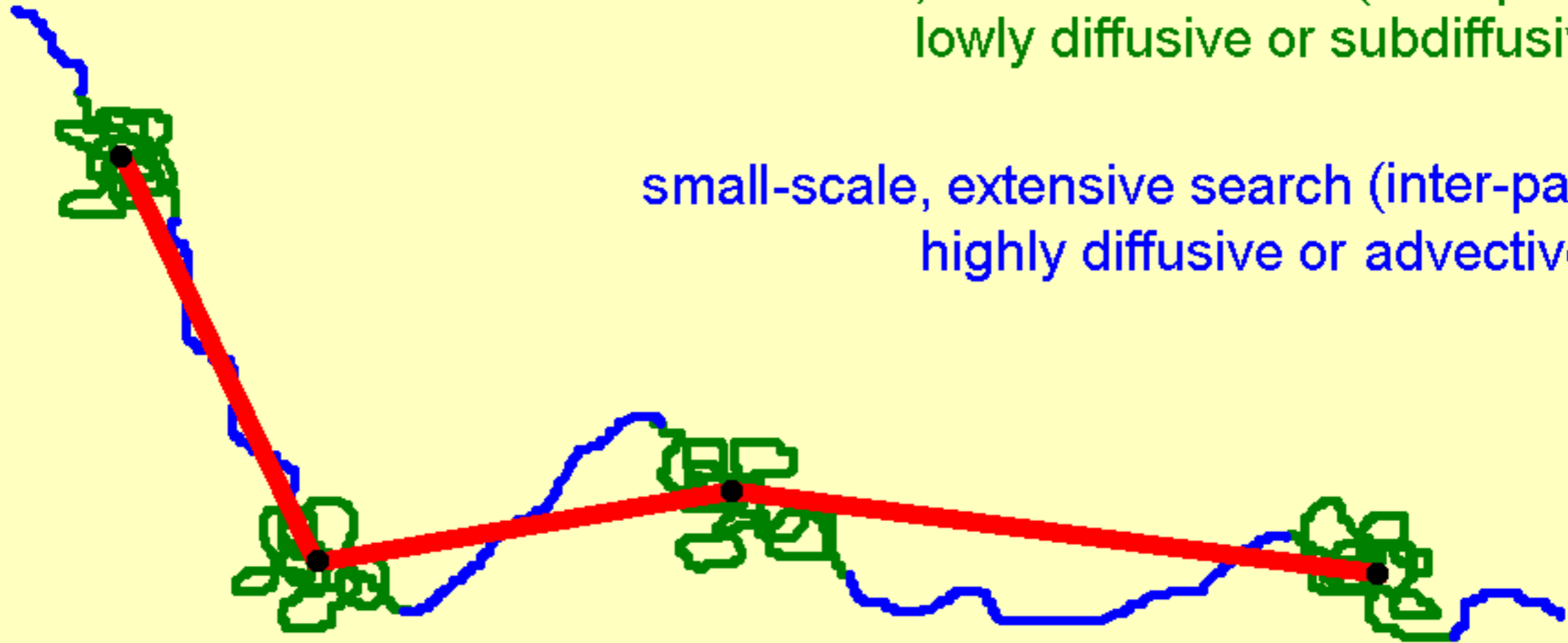
small-scale, extensive search (inter-patch):
highly diffusive or advective



Sequential search modes and simultaneous spatial scales

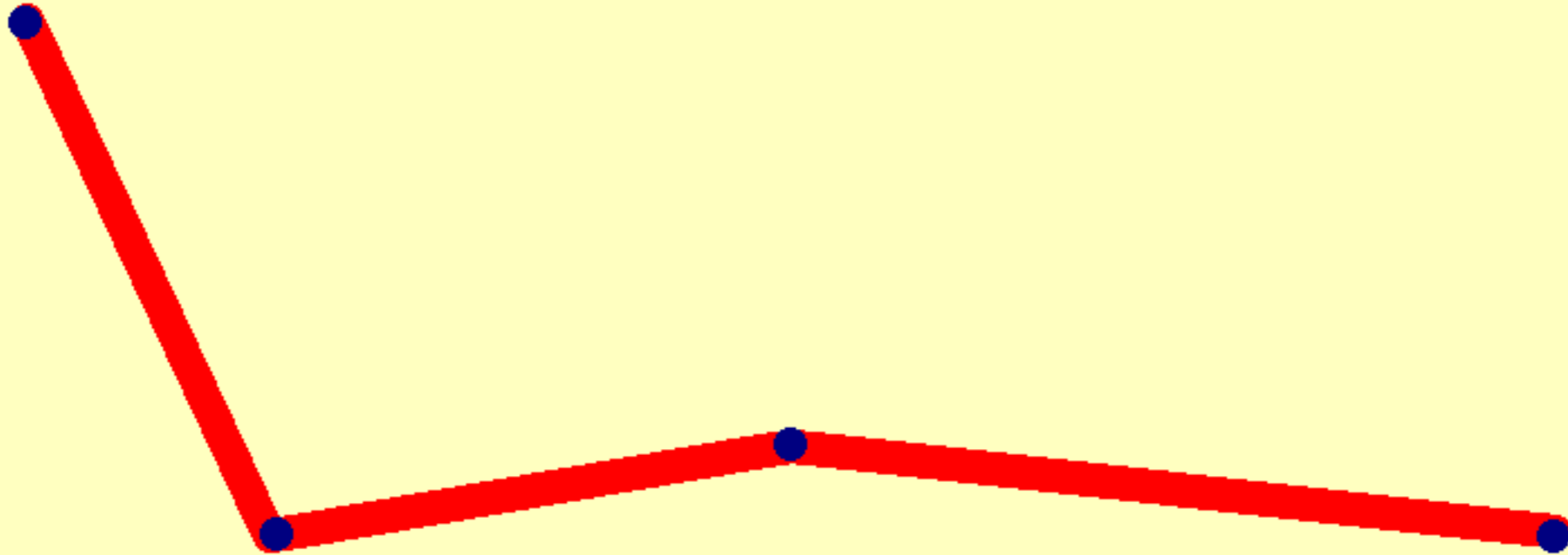
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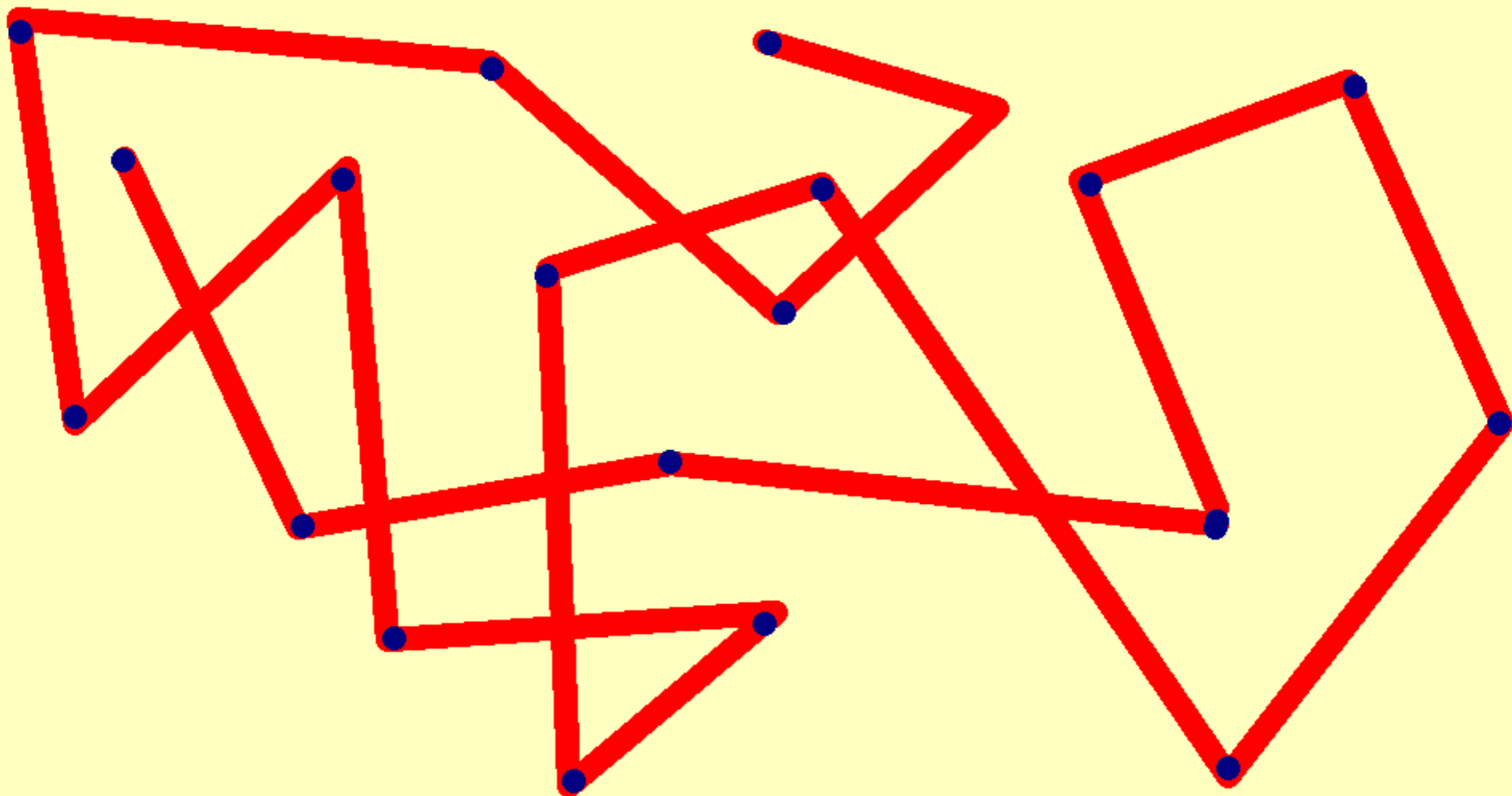


large-scale movement (sequence of visited patches):
diffusive (random search)
advective (migration)
self-constrained (home range)

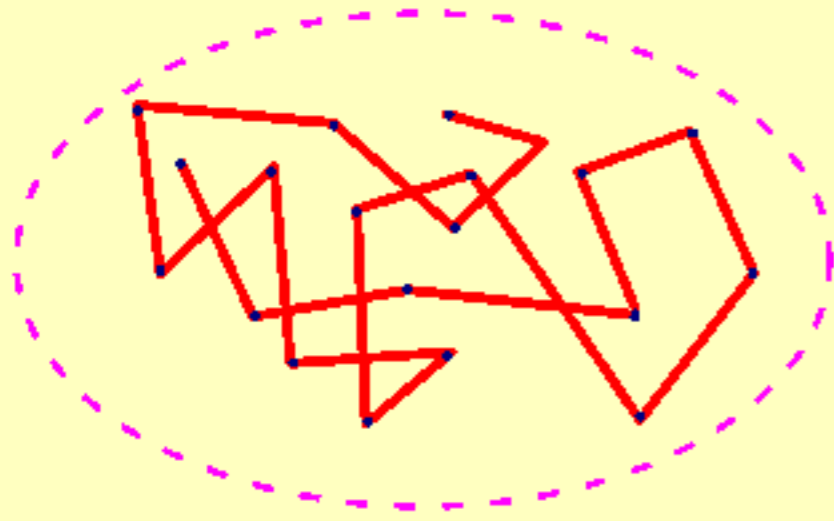
Multi-scale space-use approach



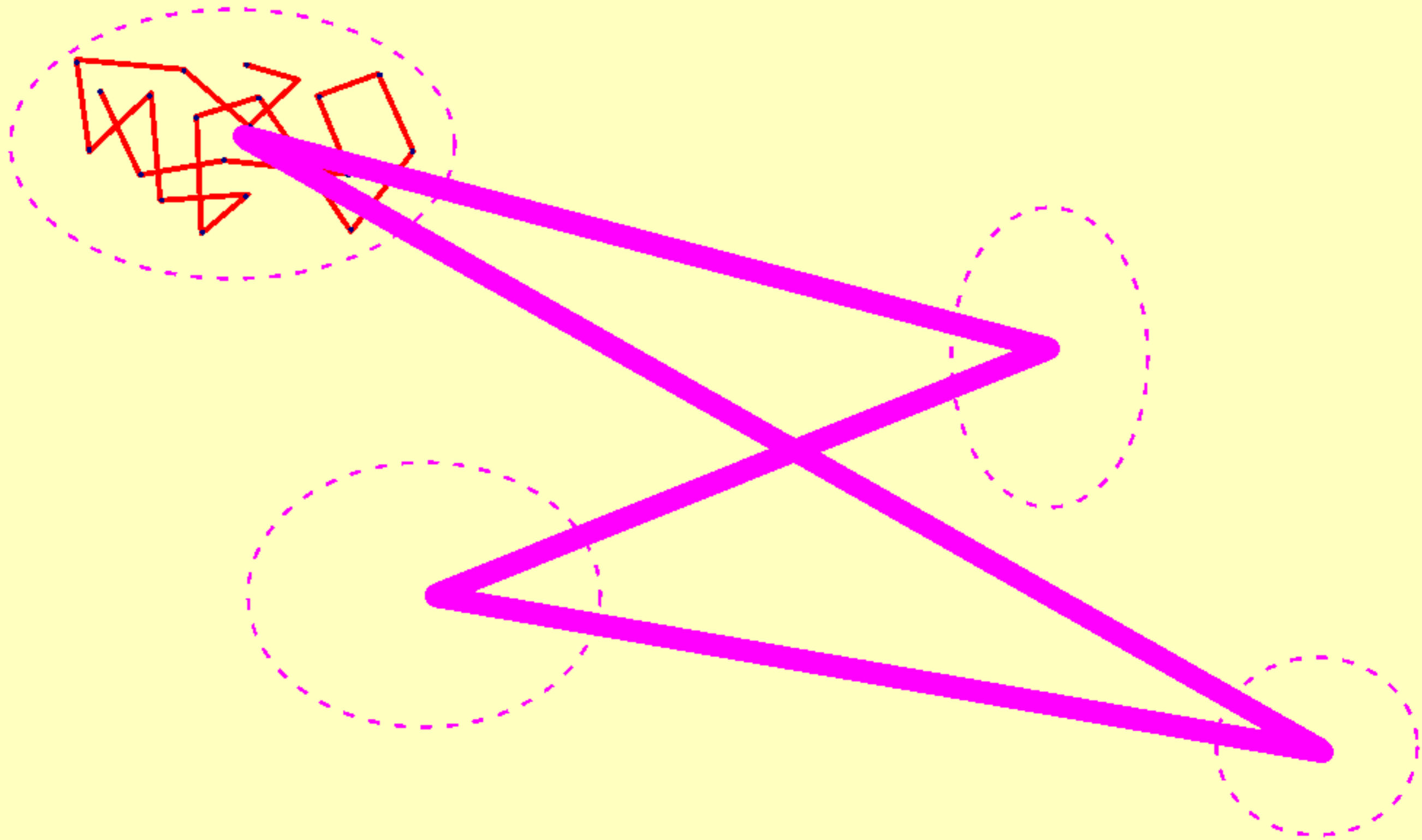
Multi-scale space-use approach



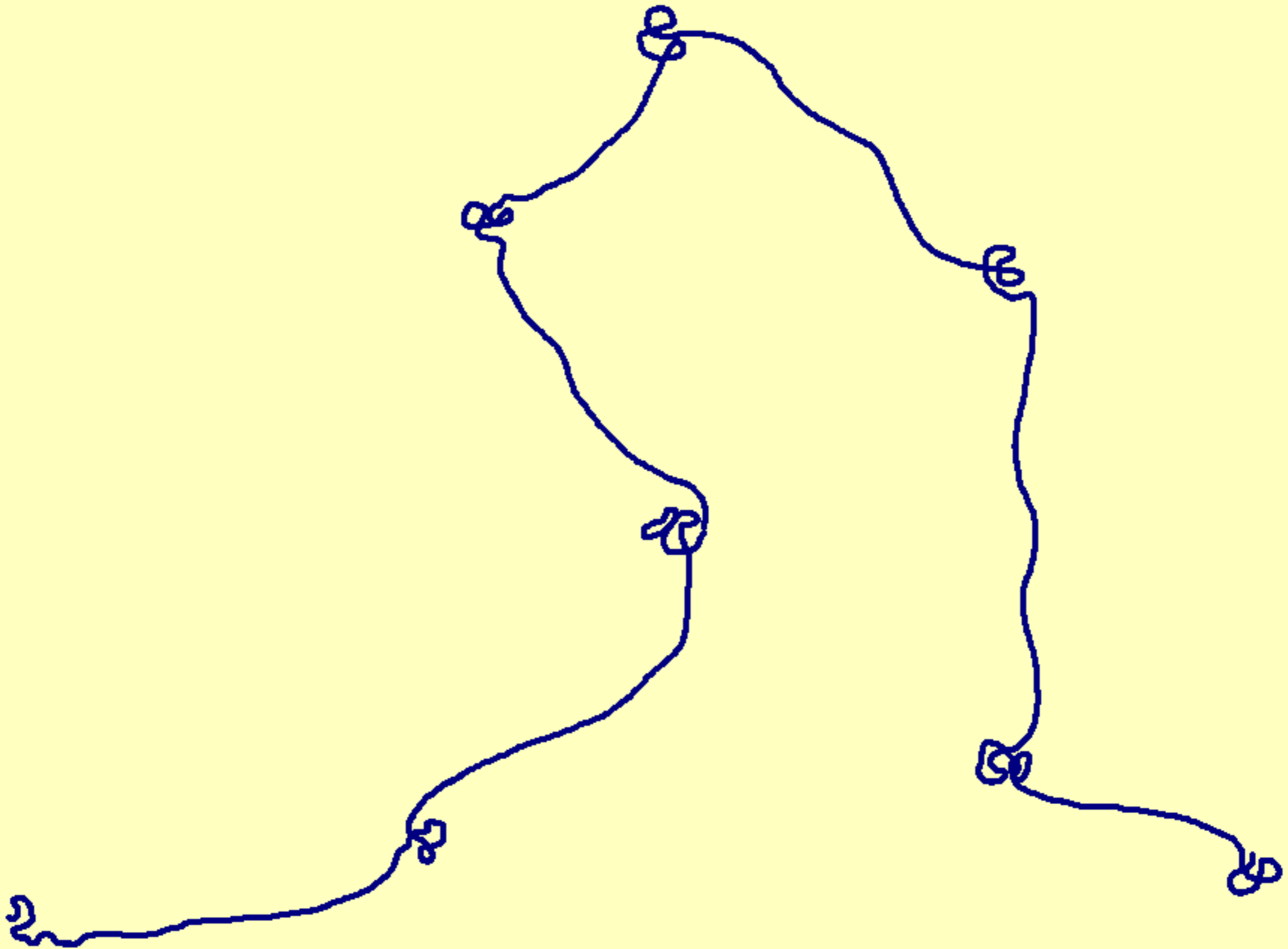
Multi-scale space-use approach

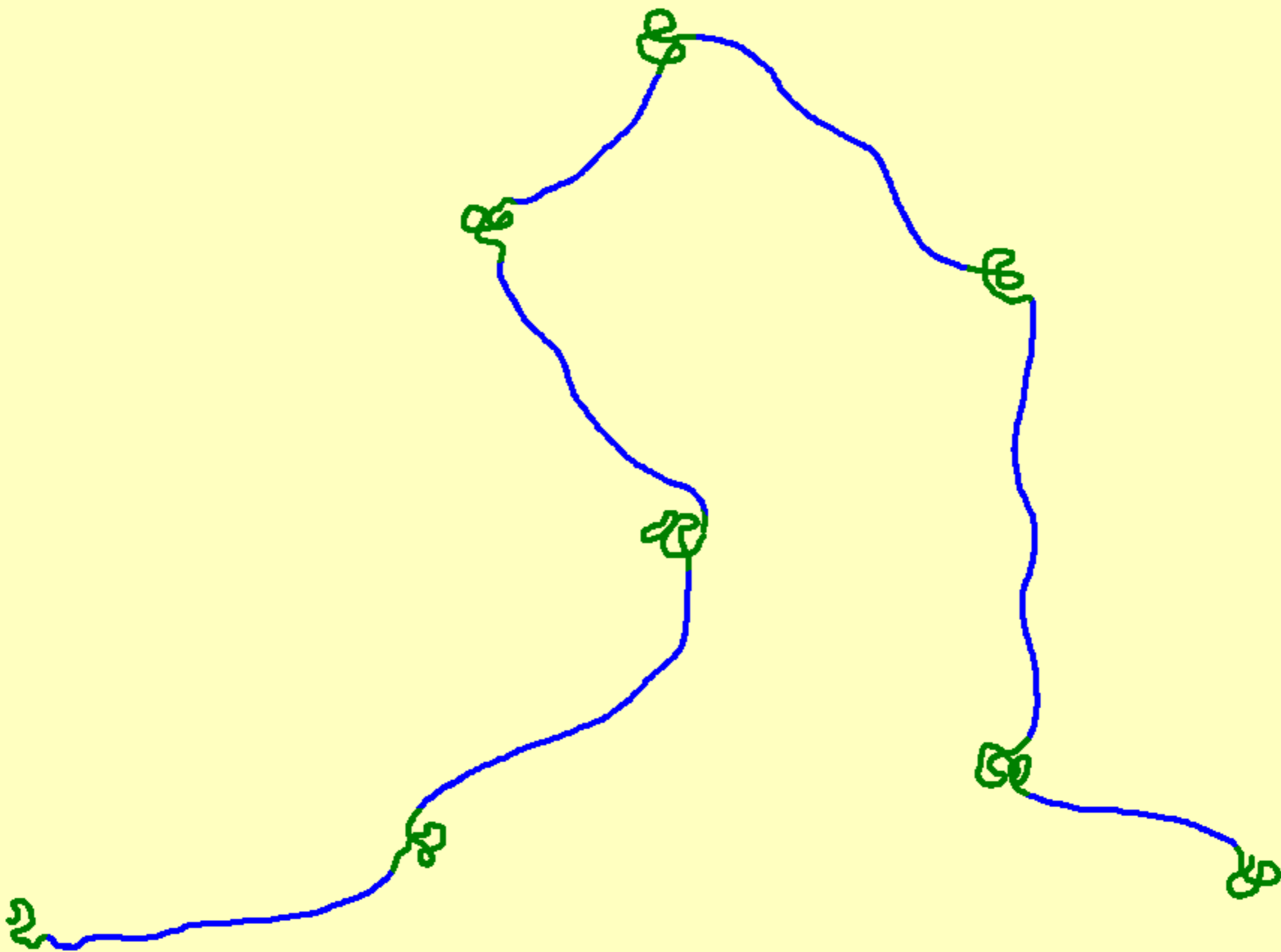


Multi-scale space-use approach



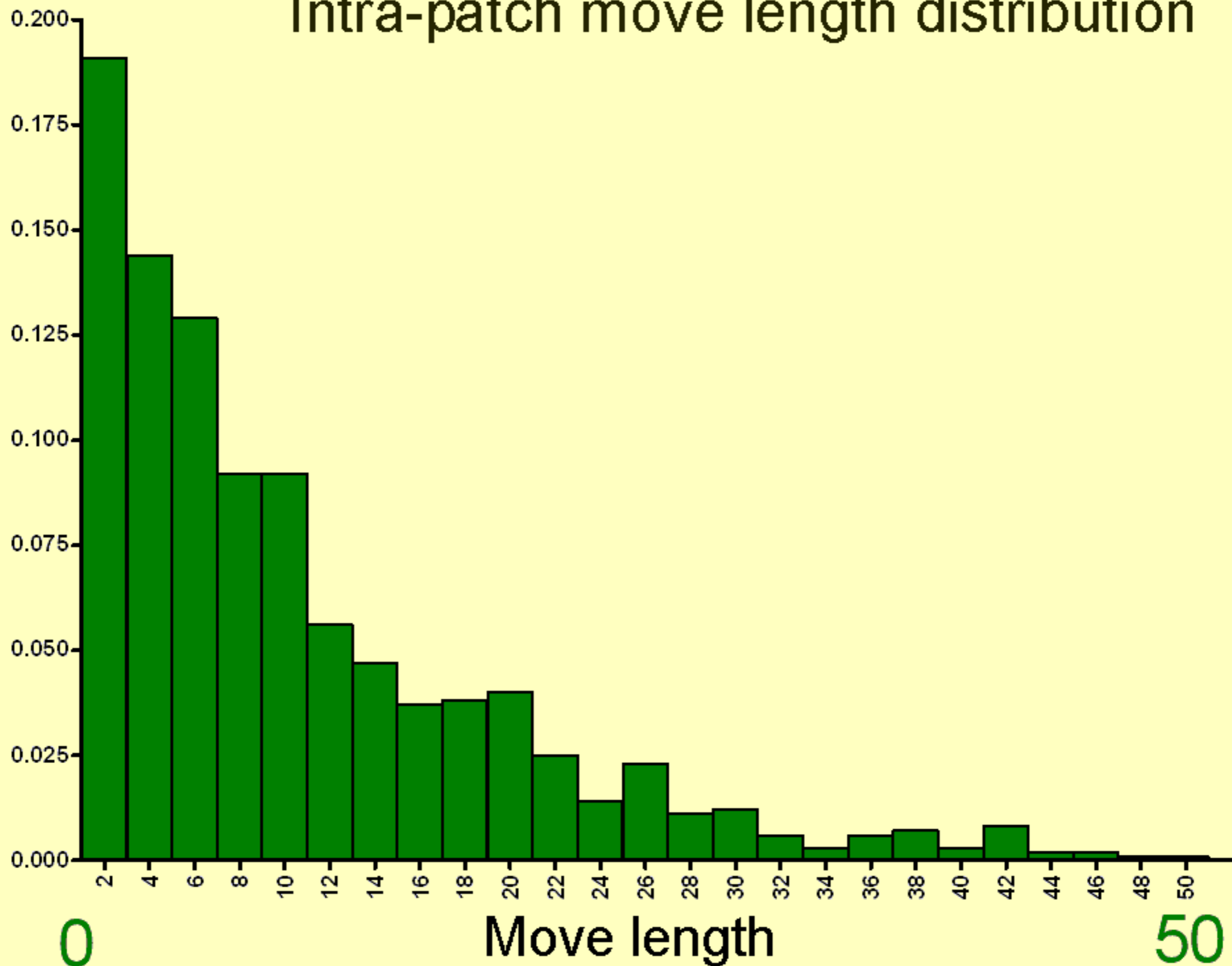
Back to basics





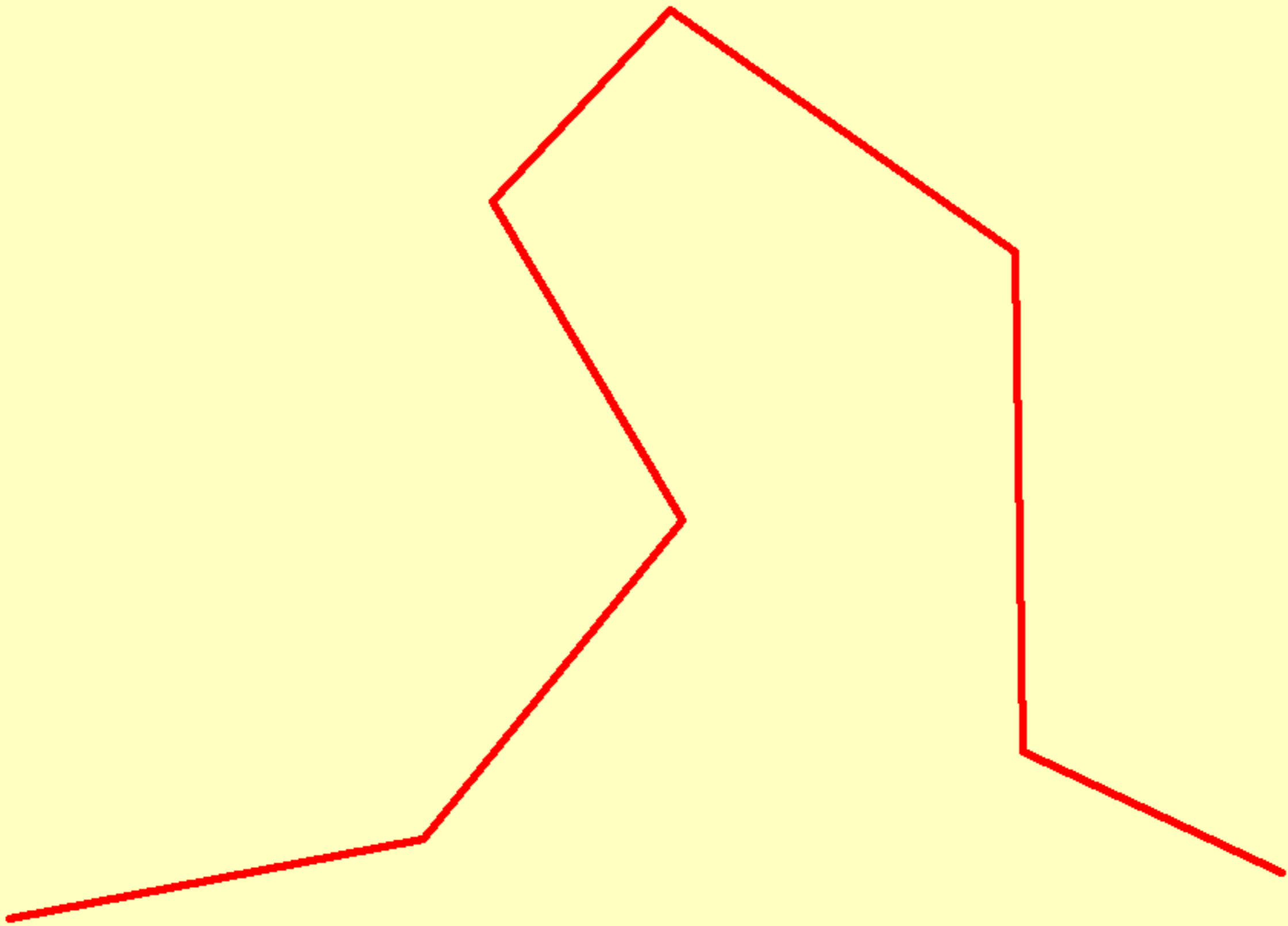
Intra-patch move length distribution

Relative frequency



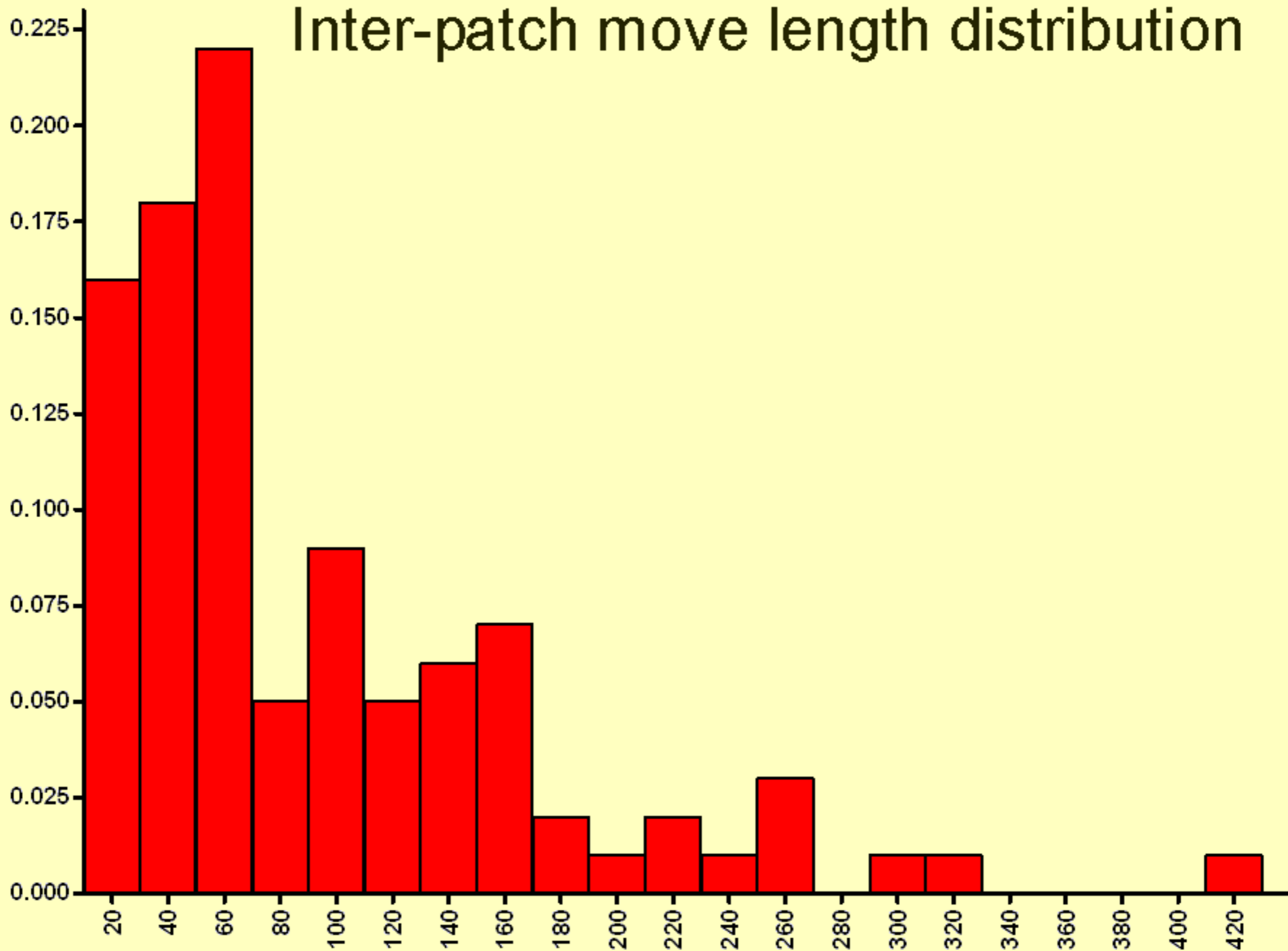
0

50



Inter-patch move length distribution

Relative frequency

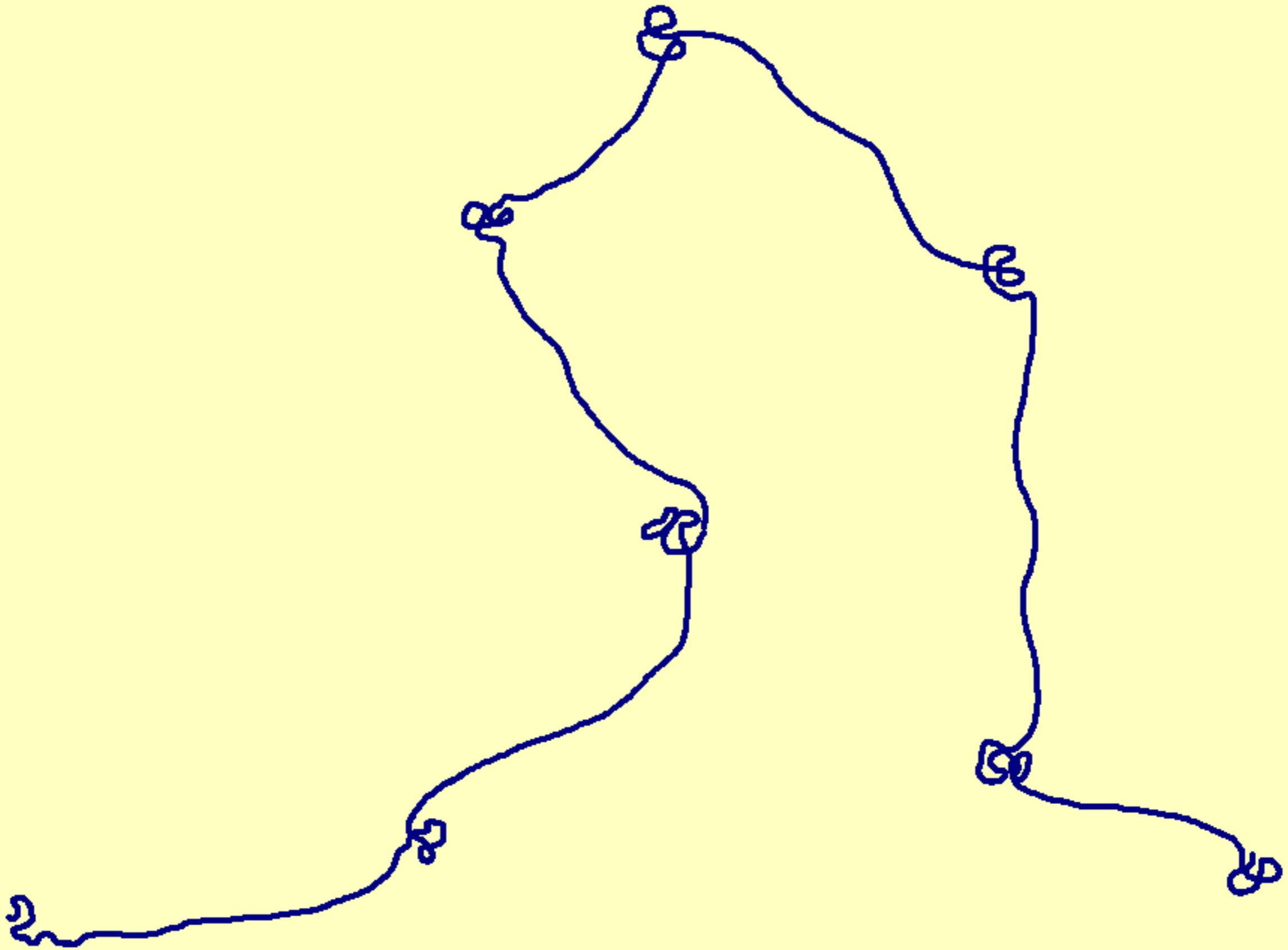


0

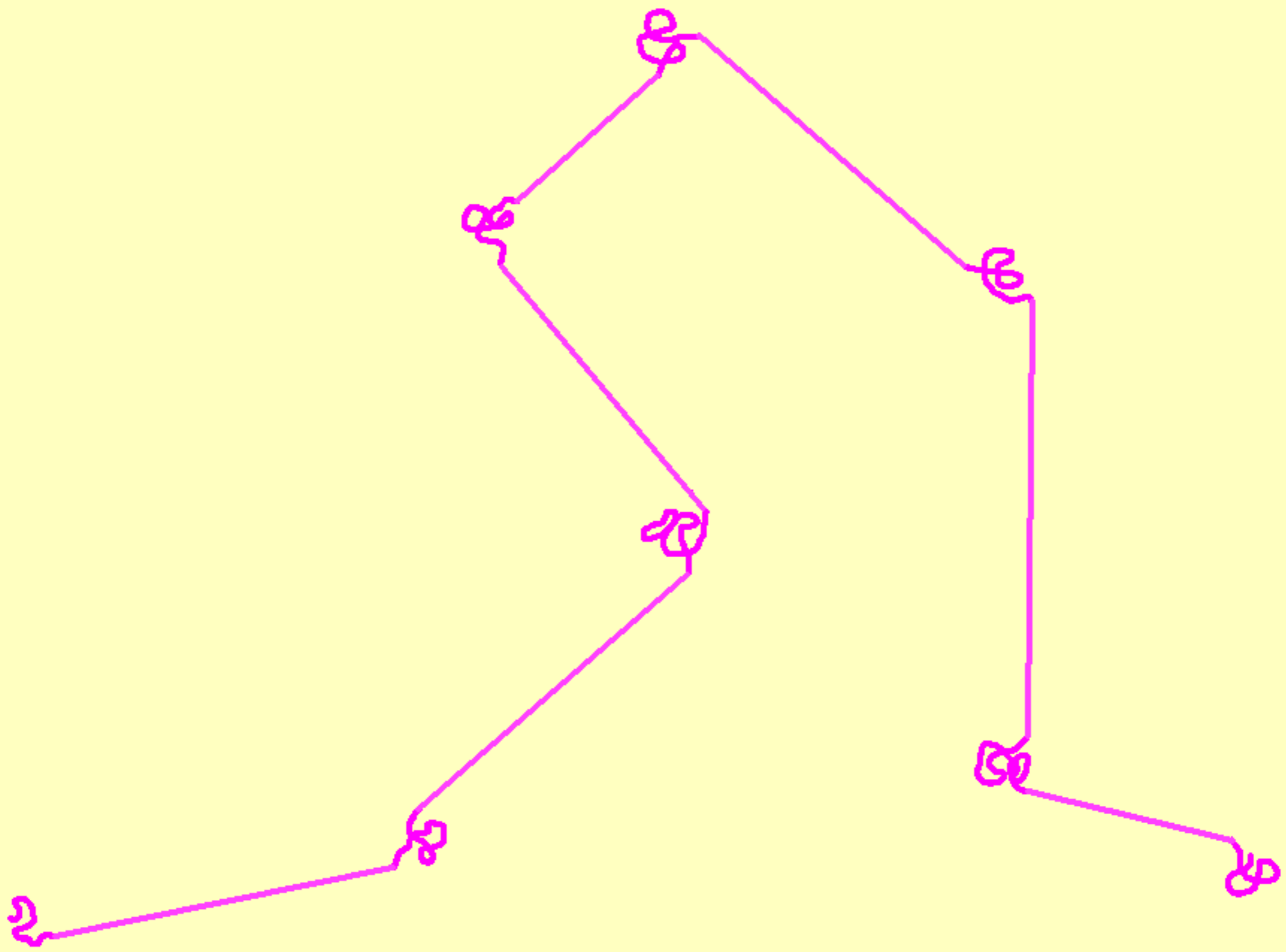
Move length

430

Using the classical but naïve "significant turn" approach ...

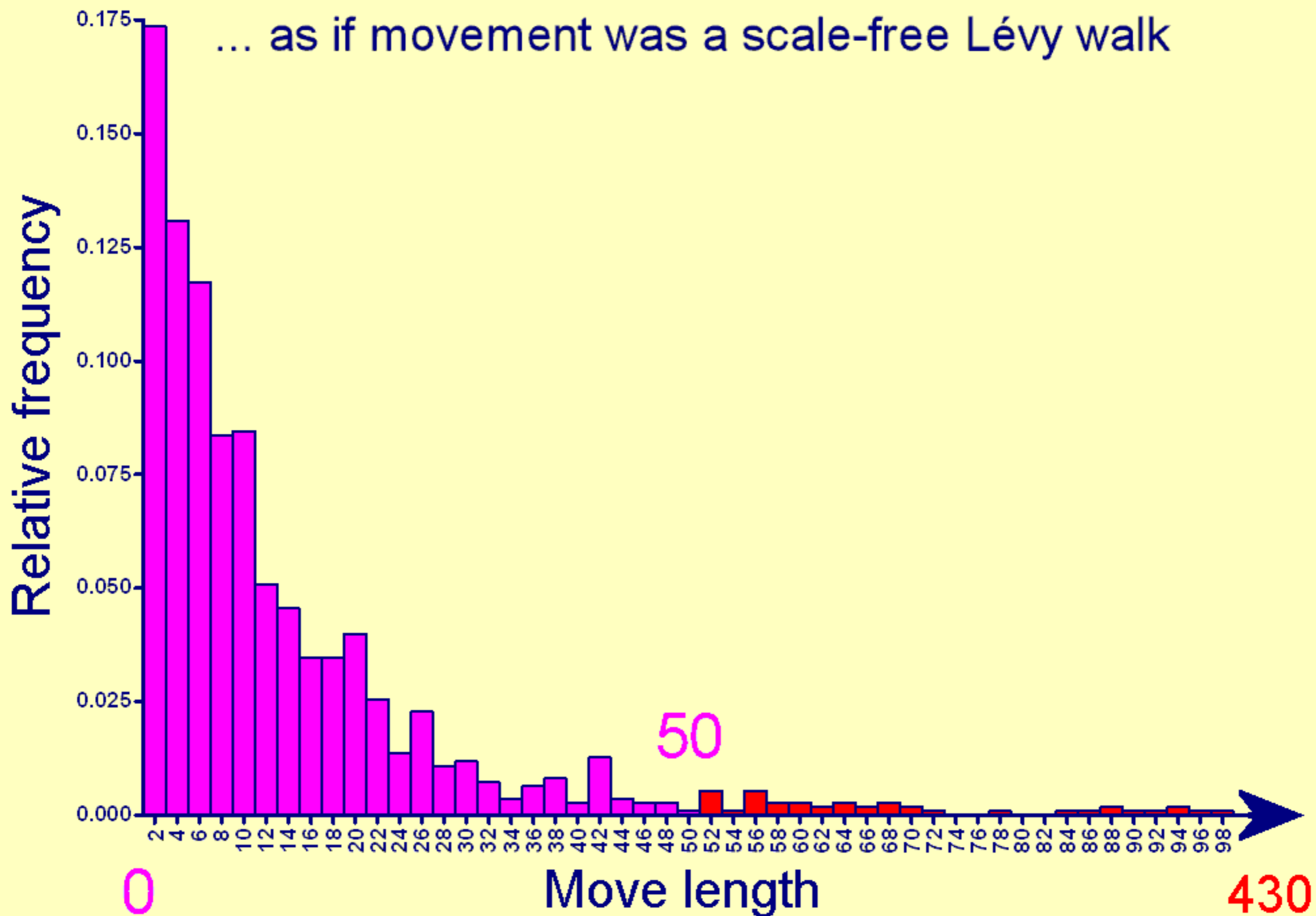


... results in a strange two-mode two-scale mixture



The resulting move length distribution seems to be heavy-tailed

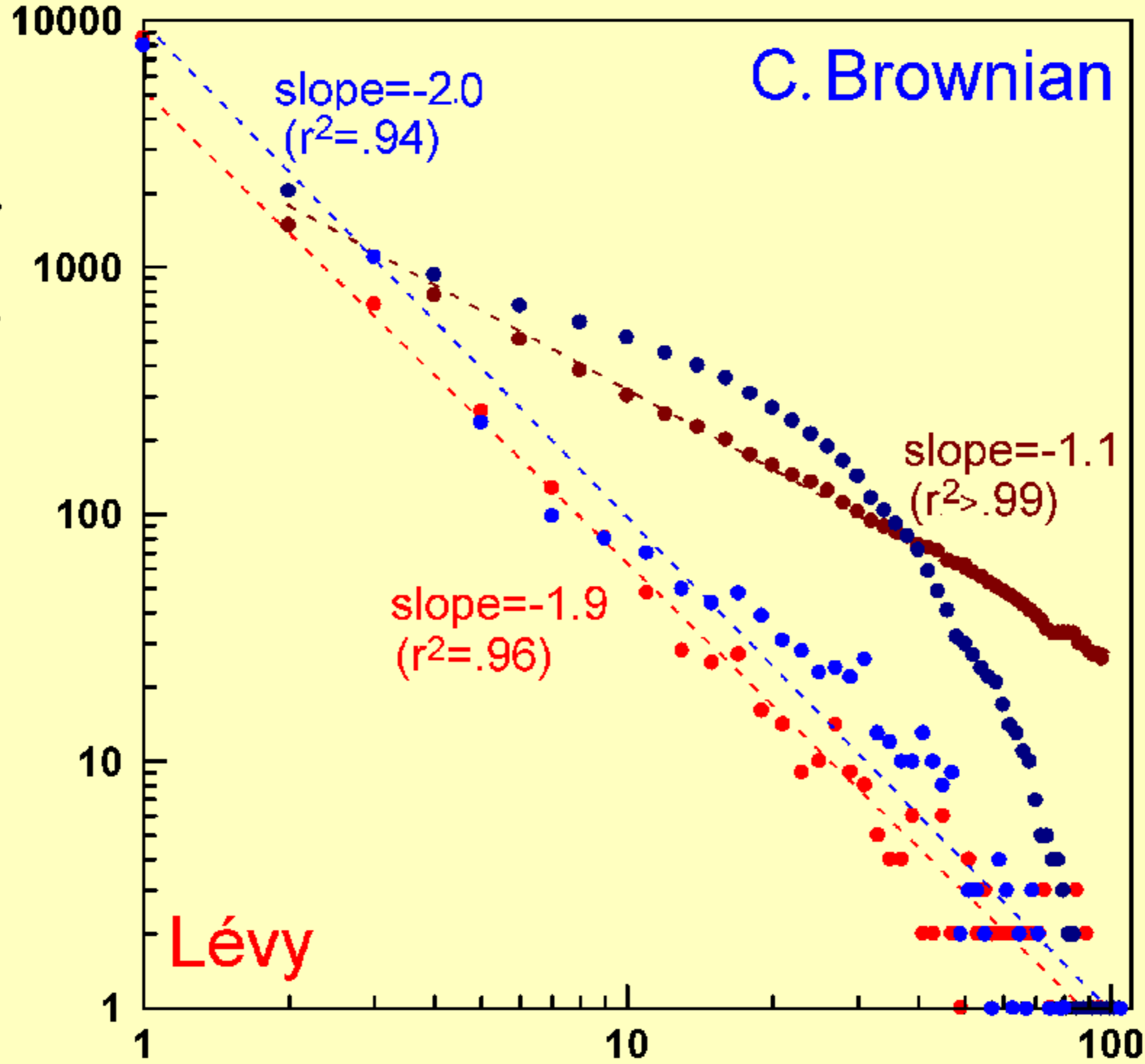
... as if movement was a scale-free Lévy walk



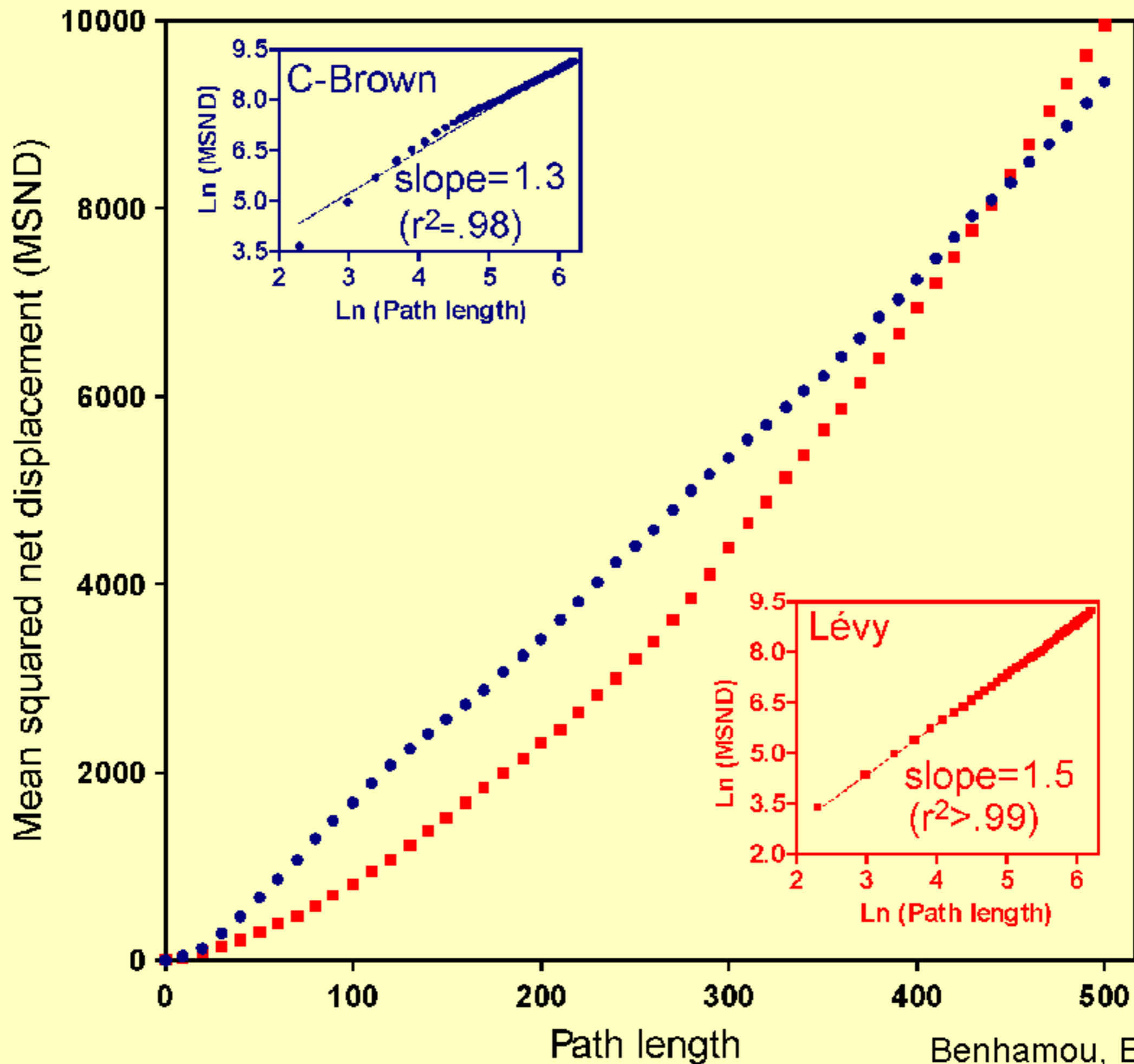
C. Brownian

Observed or Survival frequency

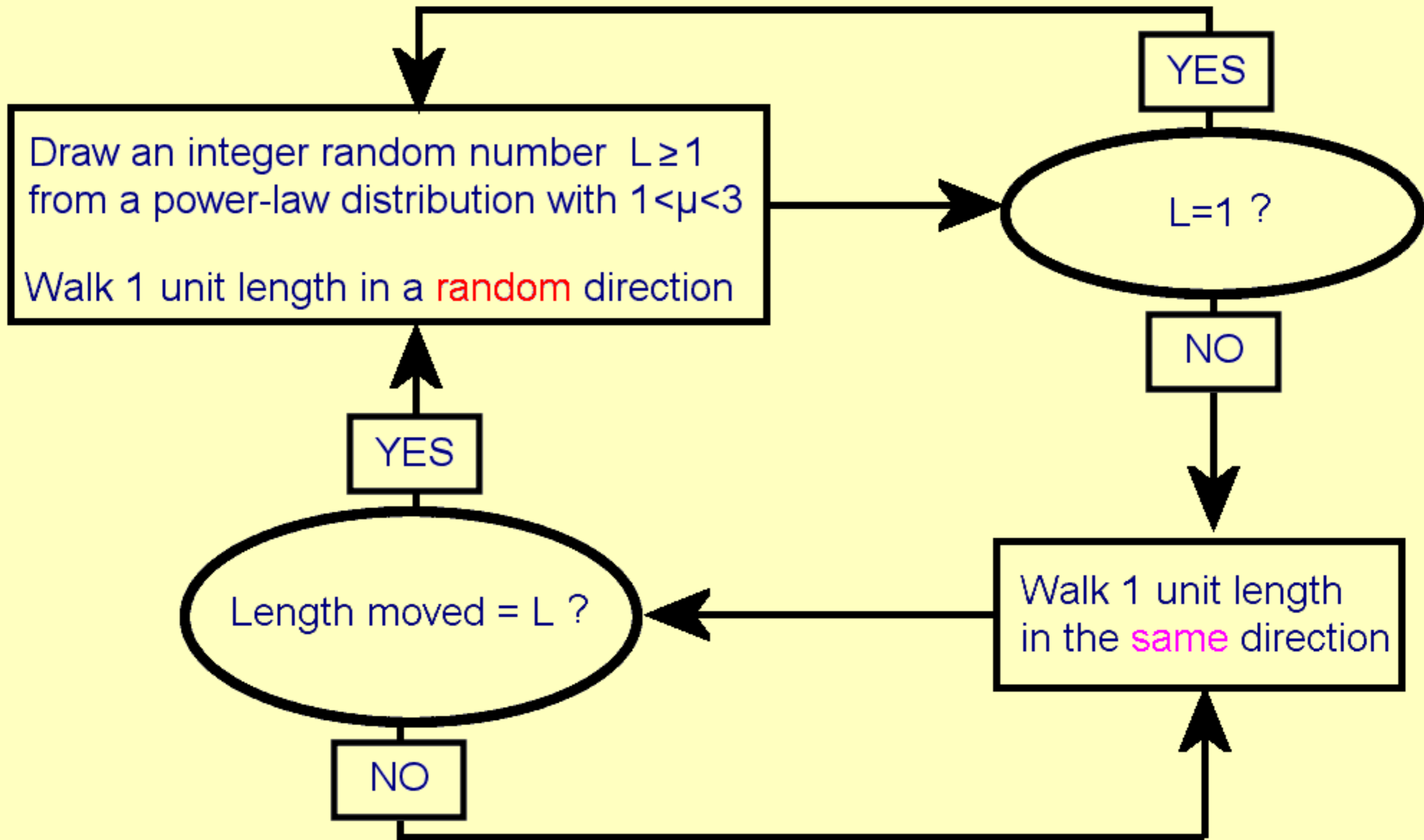
Observed or Survival frequency



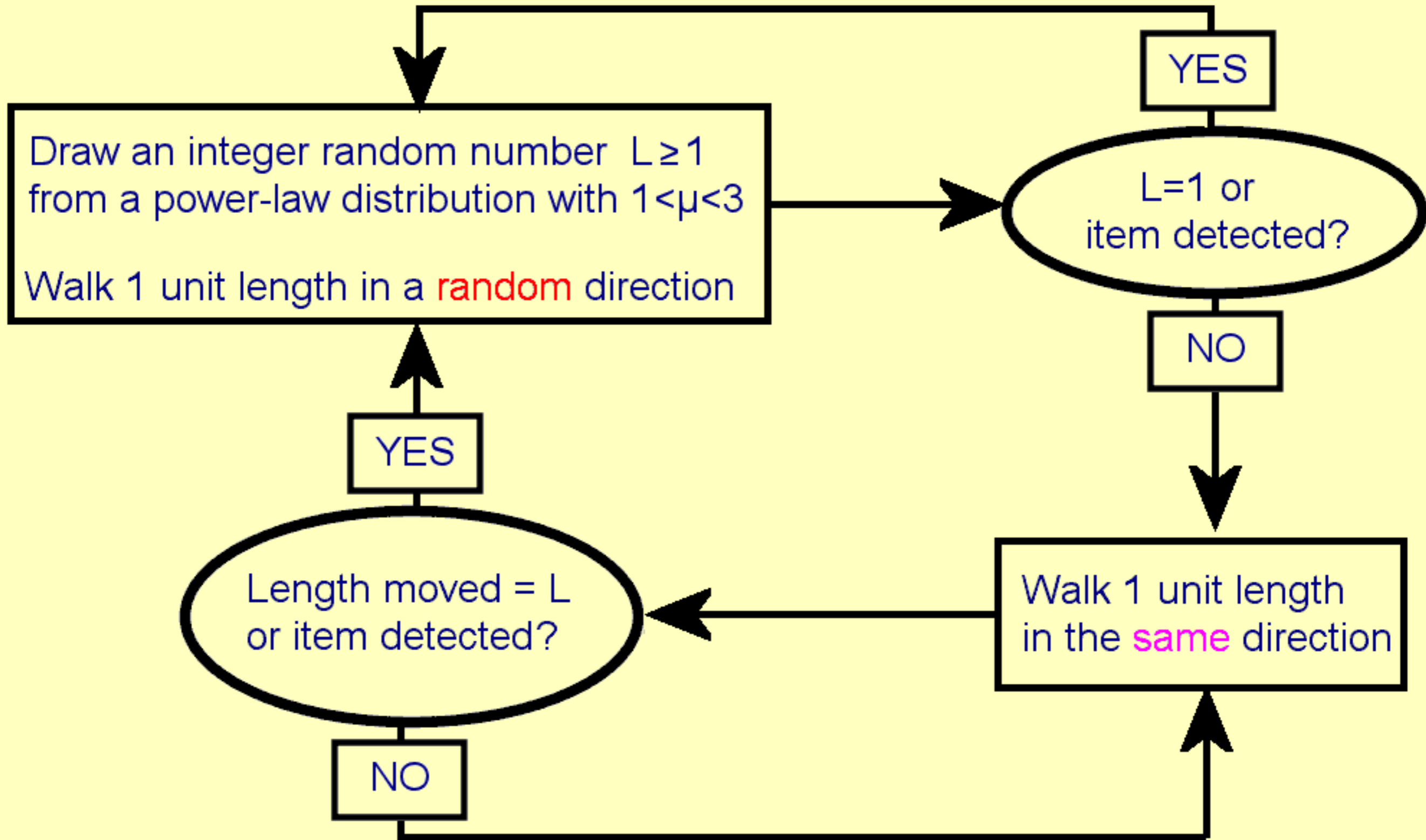
Lévy



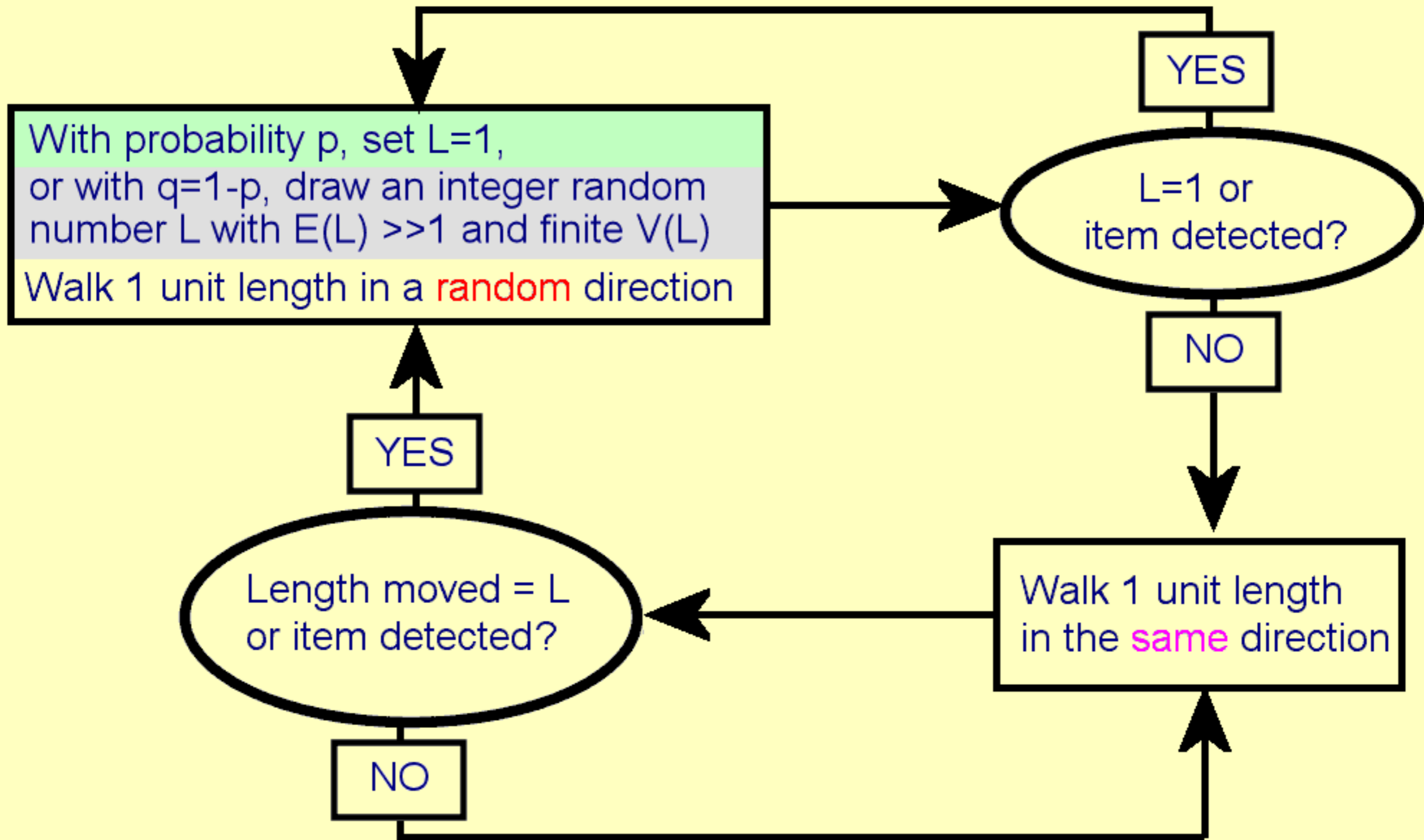
LEVY WALK



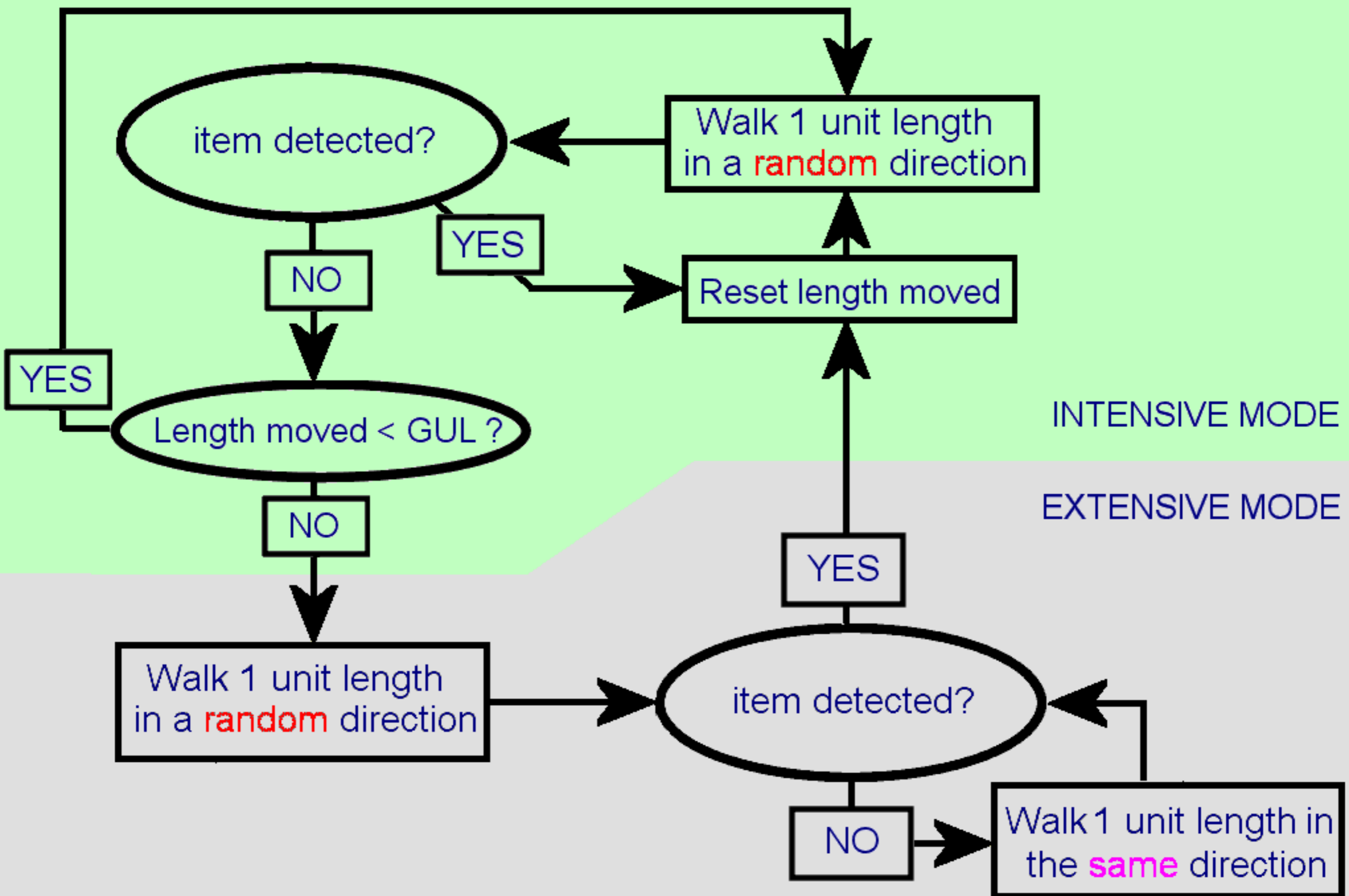
TRUNCATED LEVY WALK



TRUNCATED COMPOSITE BROWNIAN WALK



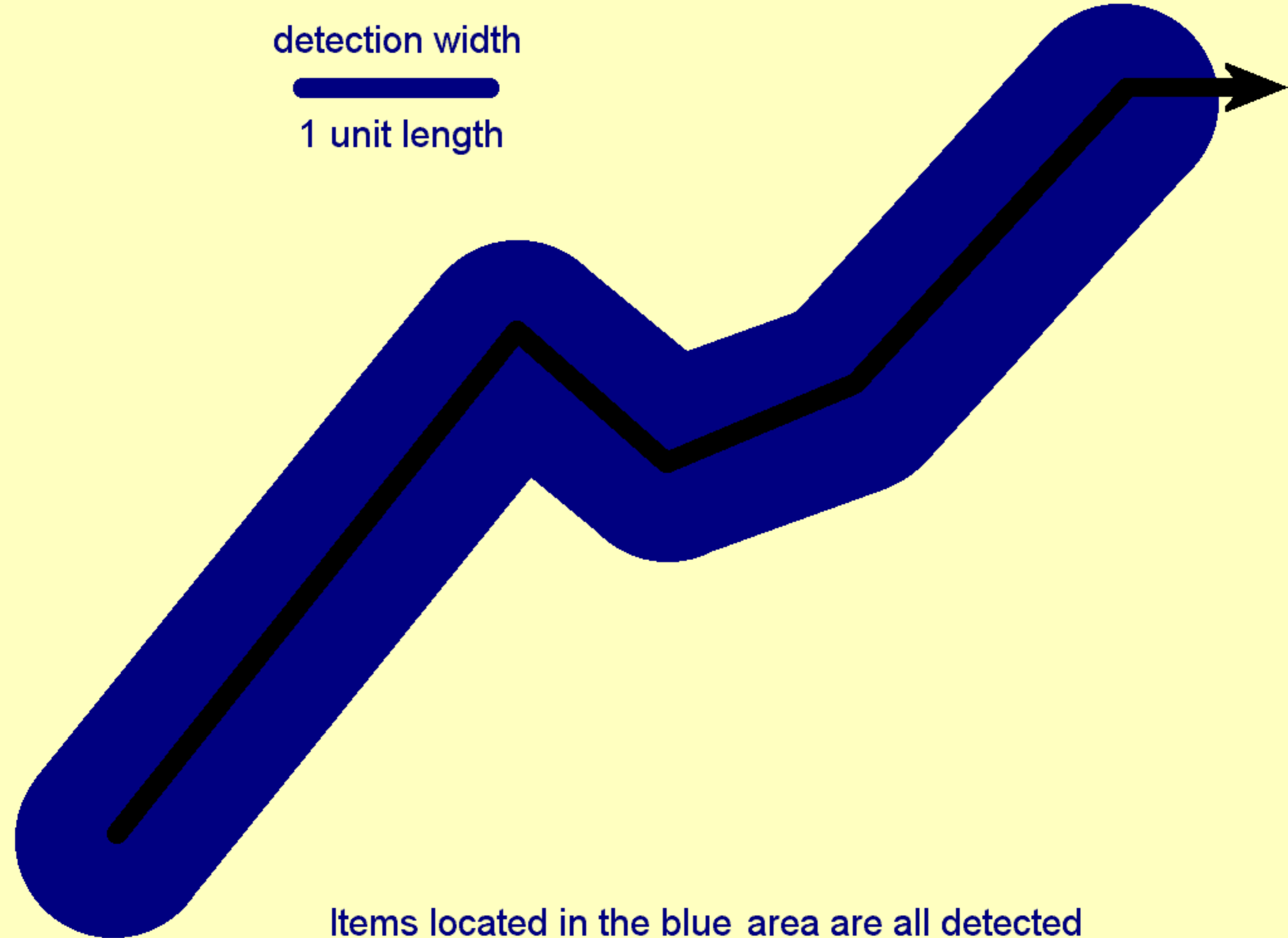
CUE-DRIVEN COMPOSITE BROWNIAN WALK



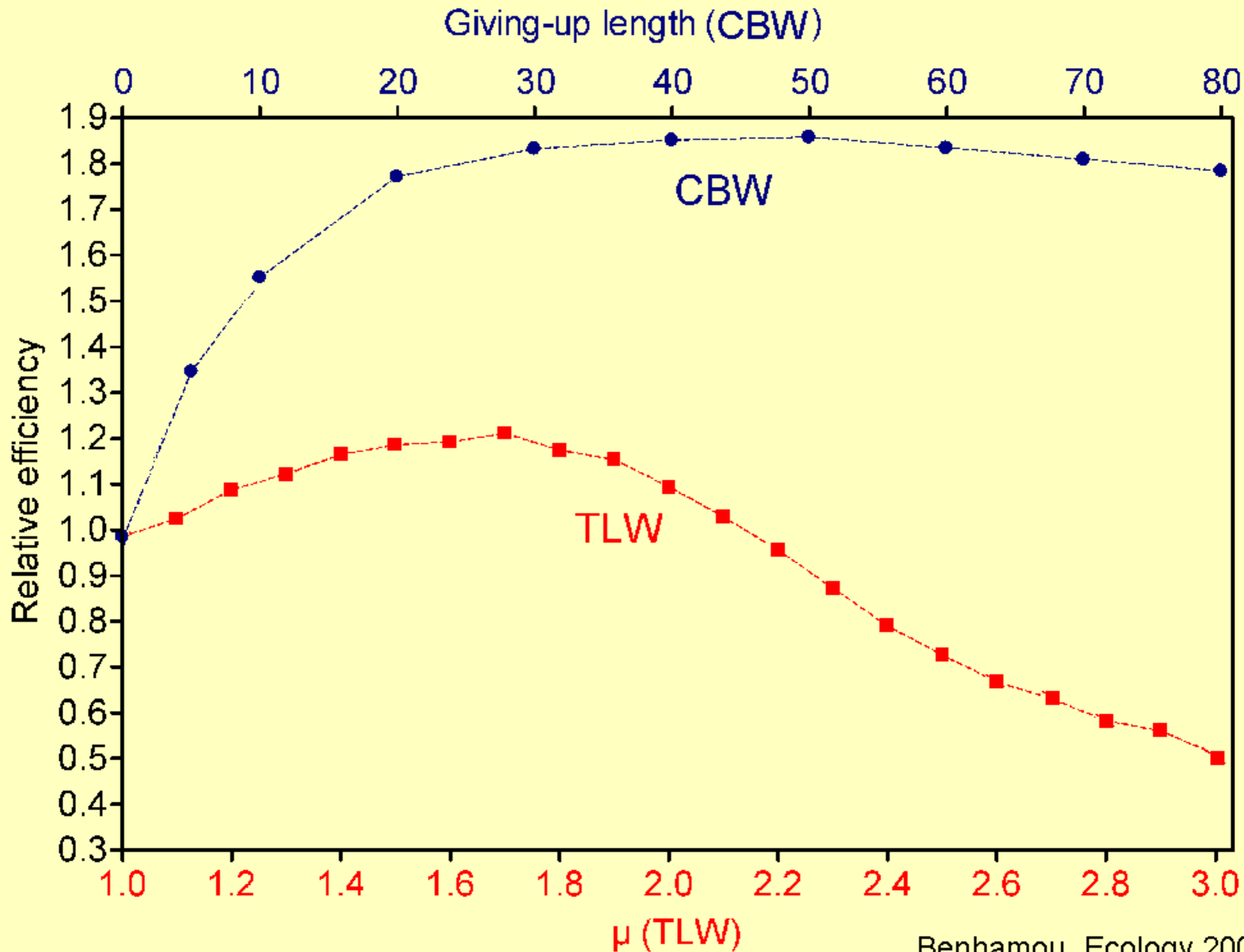
detection width



1 unit length



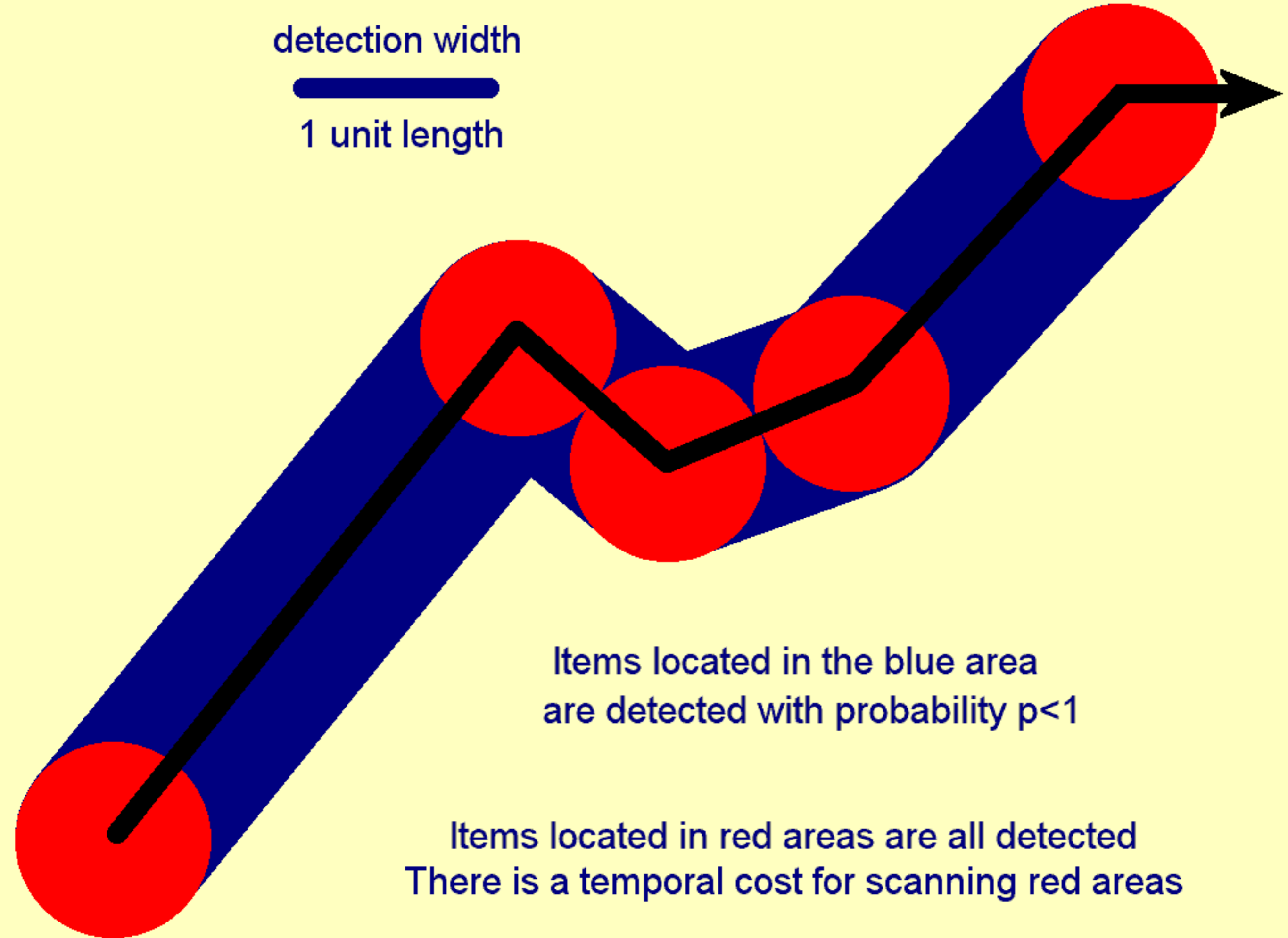
Items located in the blue area are all detected



detection width



1 unit length



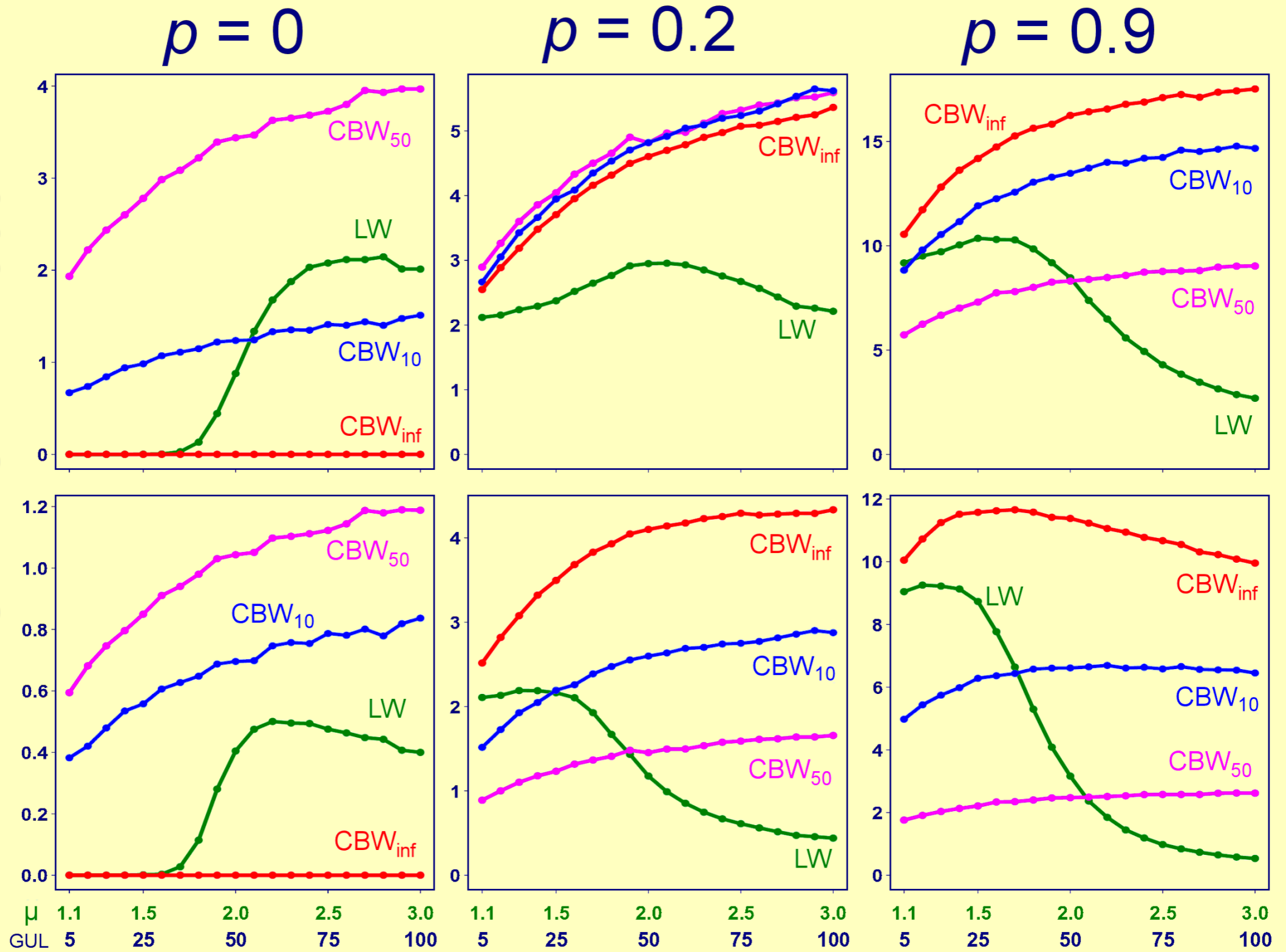
Items located in the blue area
are detected with probability $p < 1$

Items located in red areas are all detected
There is a temporal cost for scanning red areas

COST = 1

COST = 10

EFFICIENCY X 1000



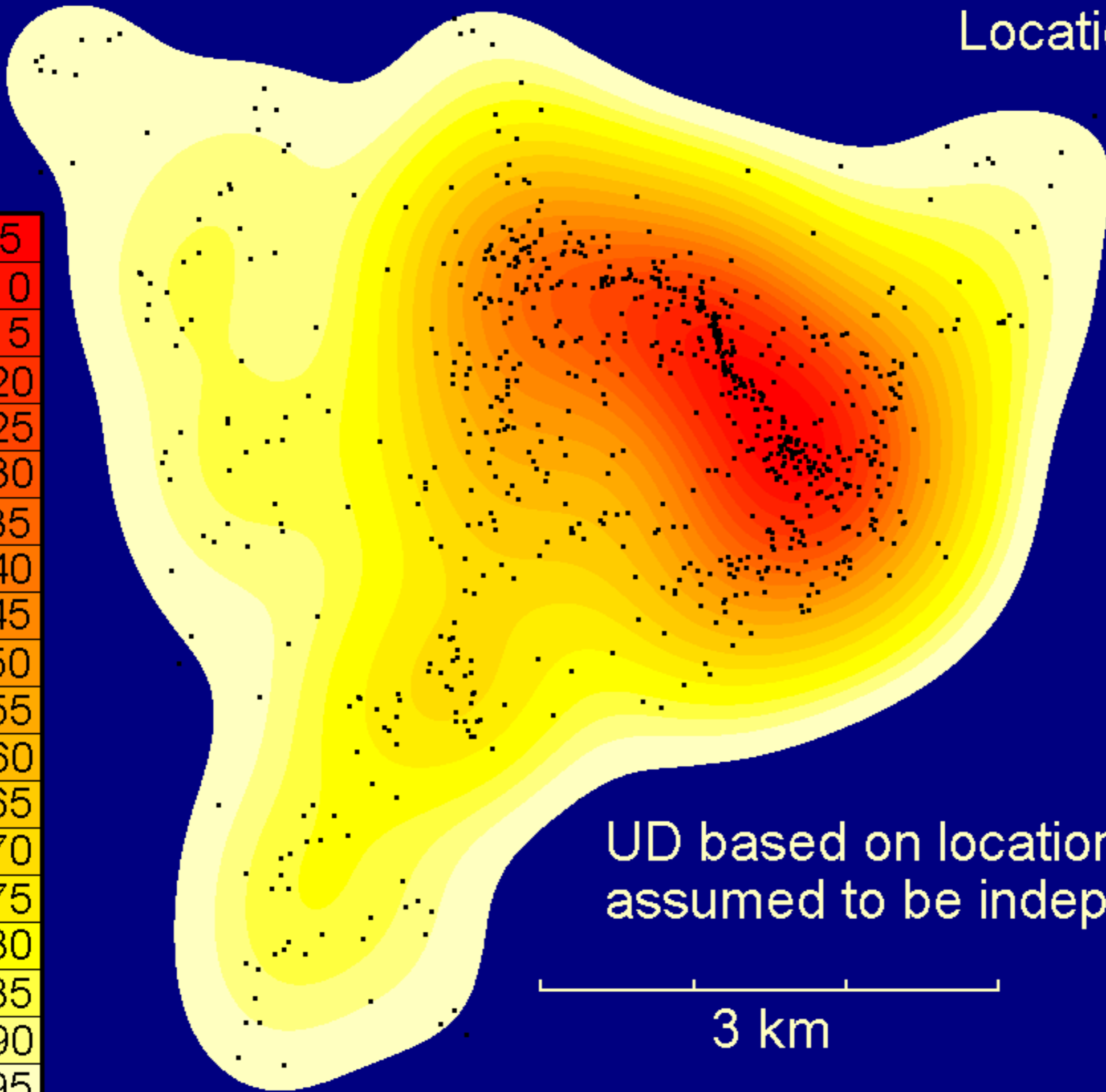
Location-based KDE



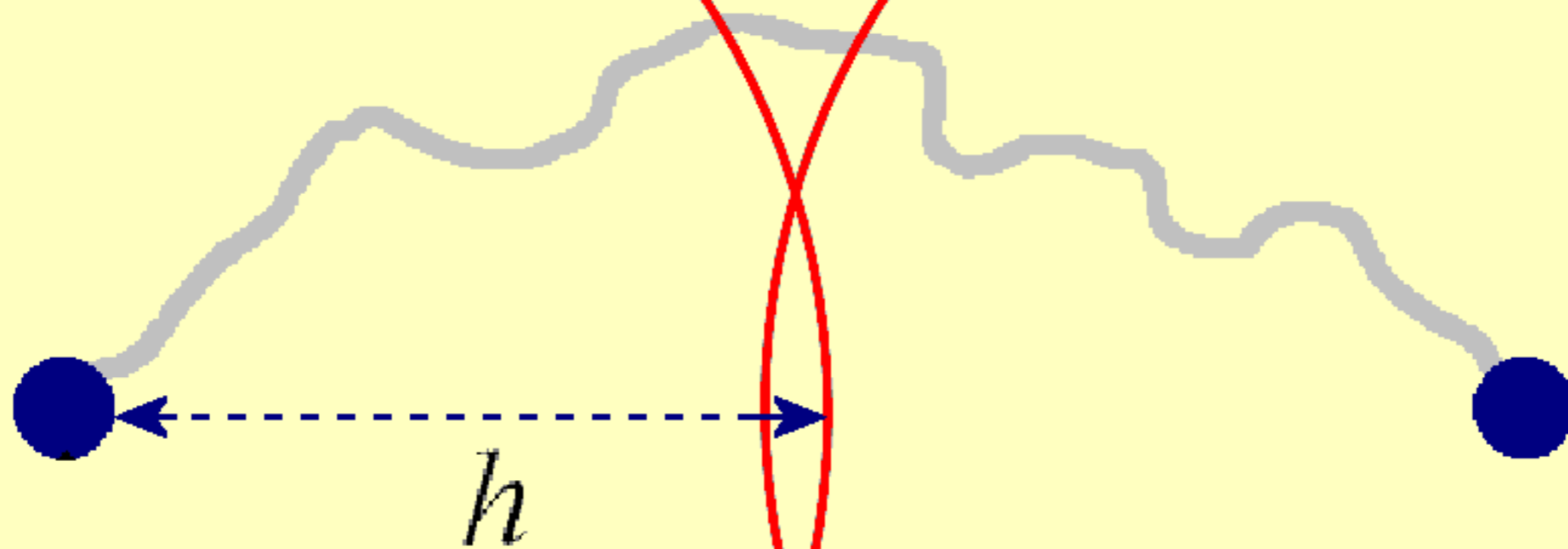
UD based on locations
assumed to be independent



$h = 500\text{ m}$

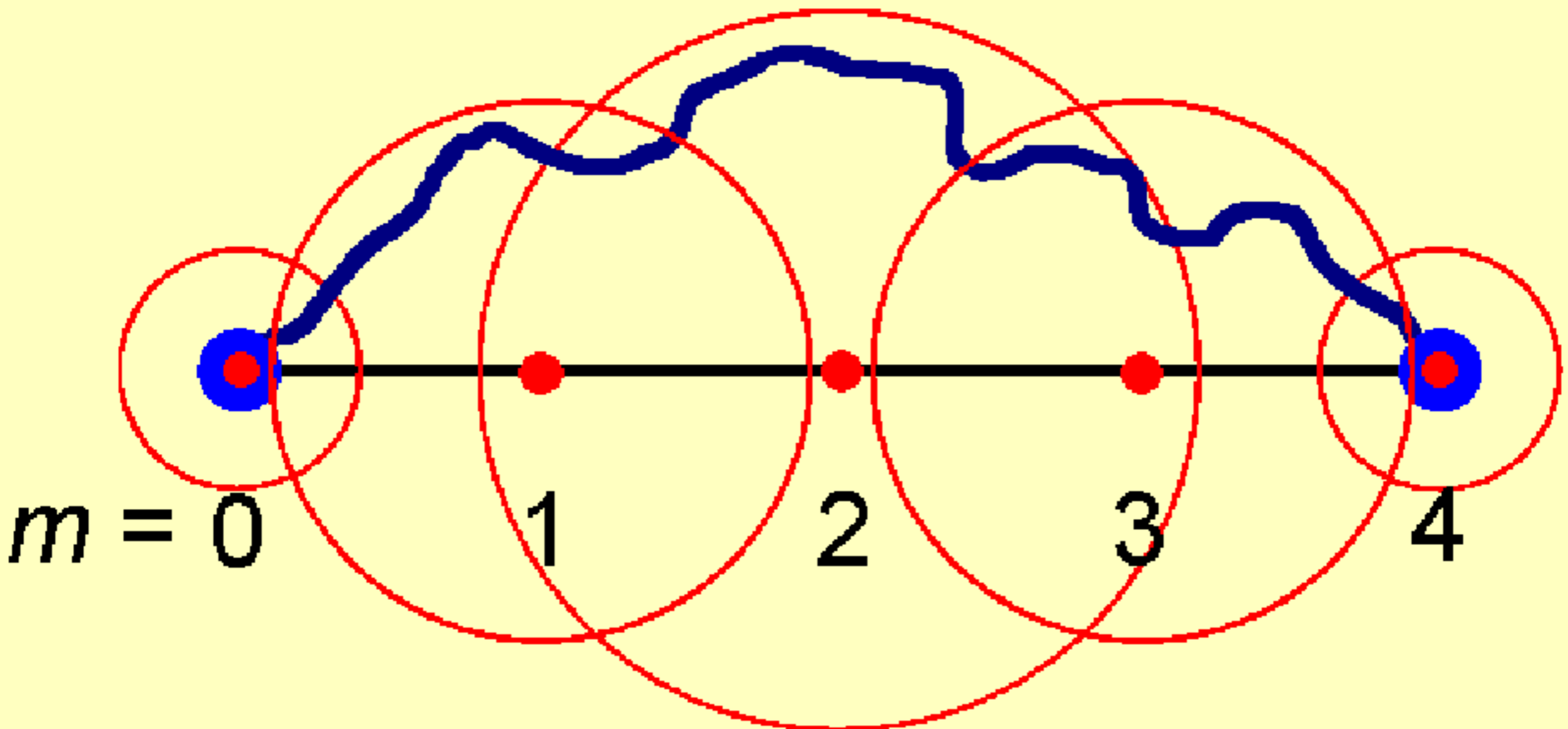


Locations assumed to be independent

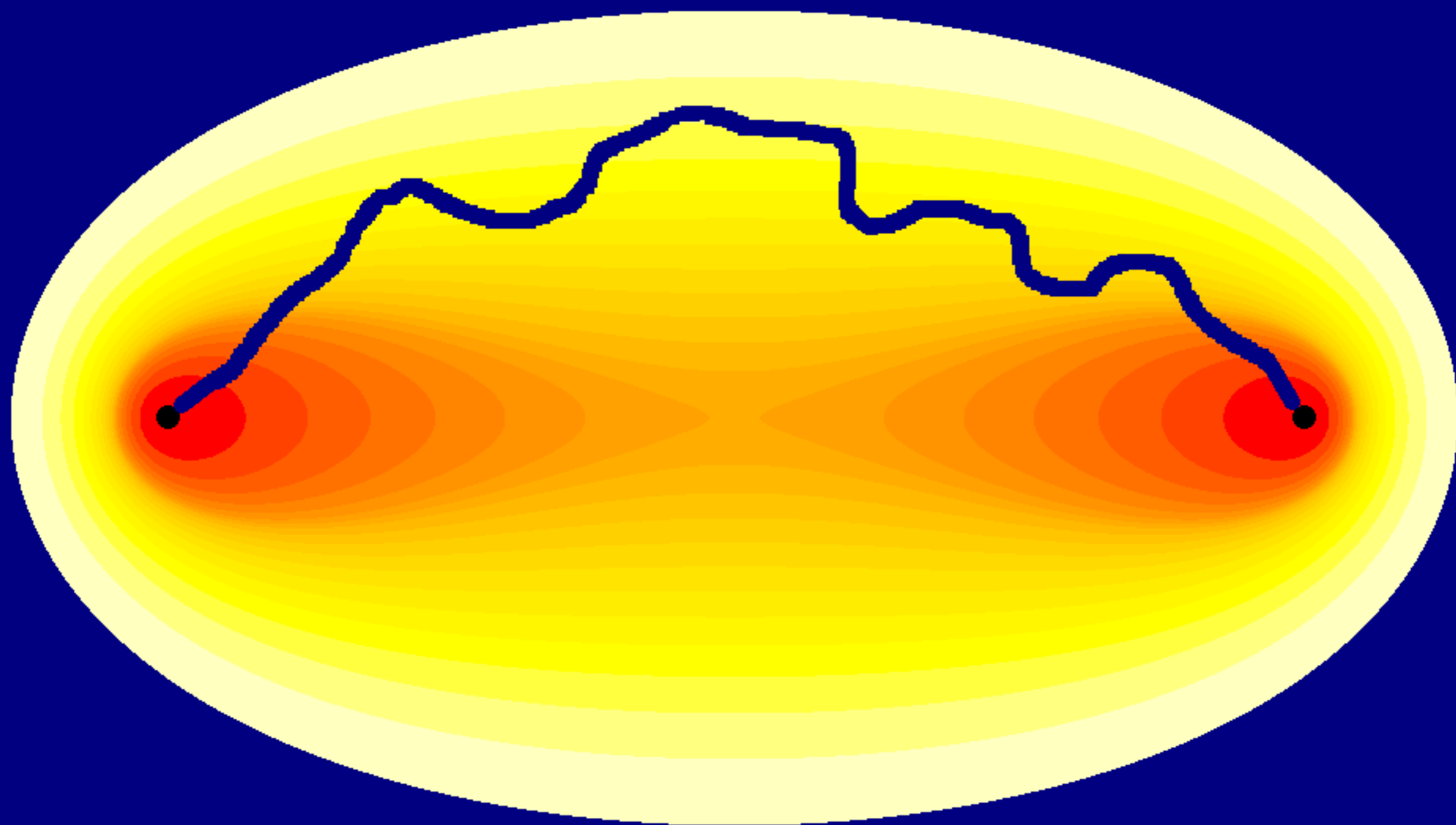


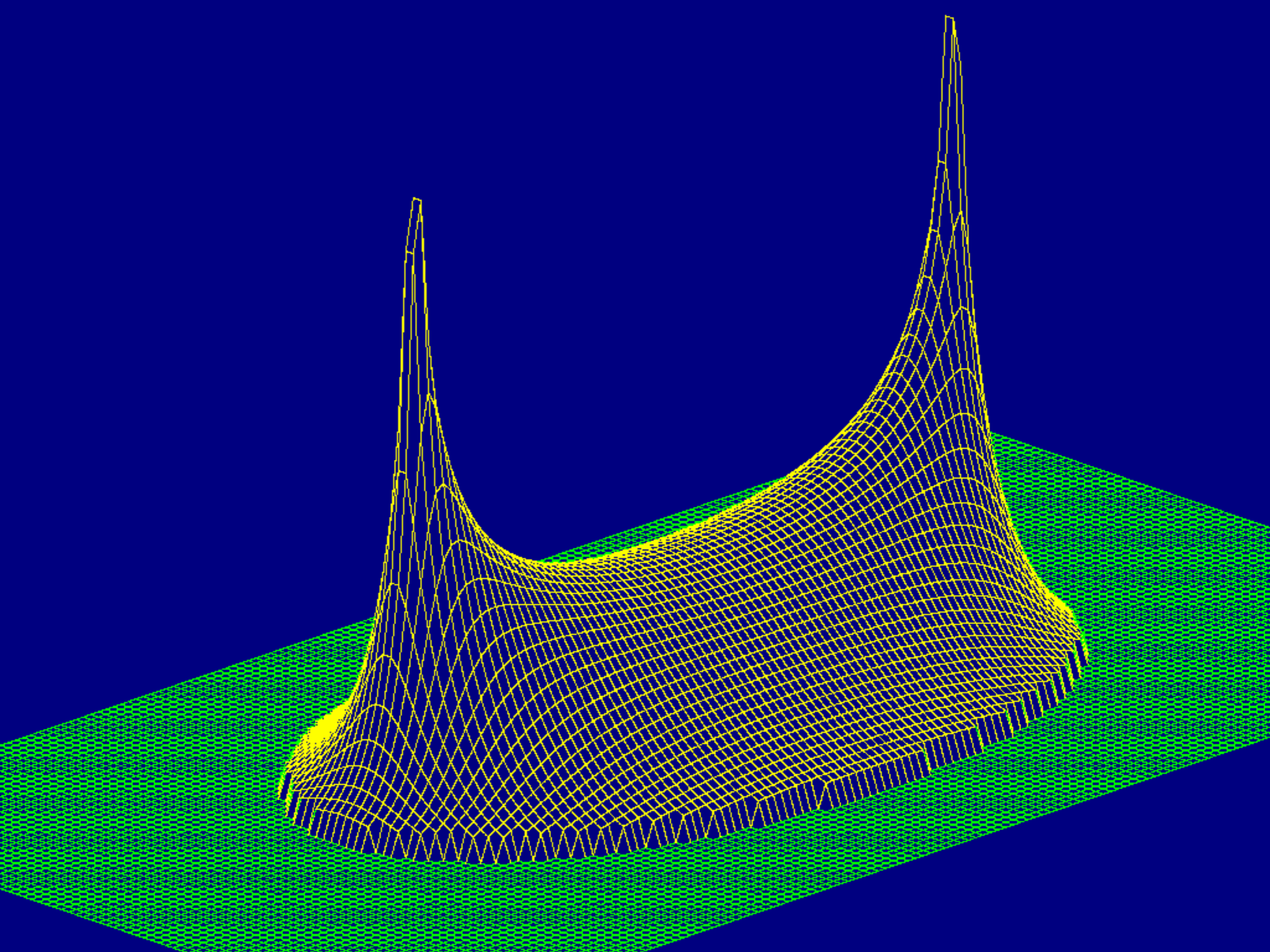
Locations interpolated with a constant activity time

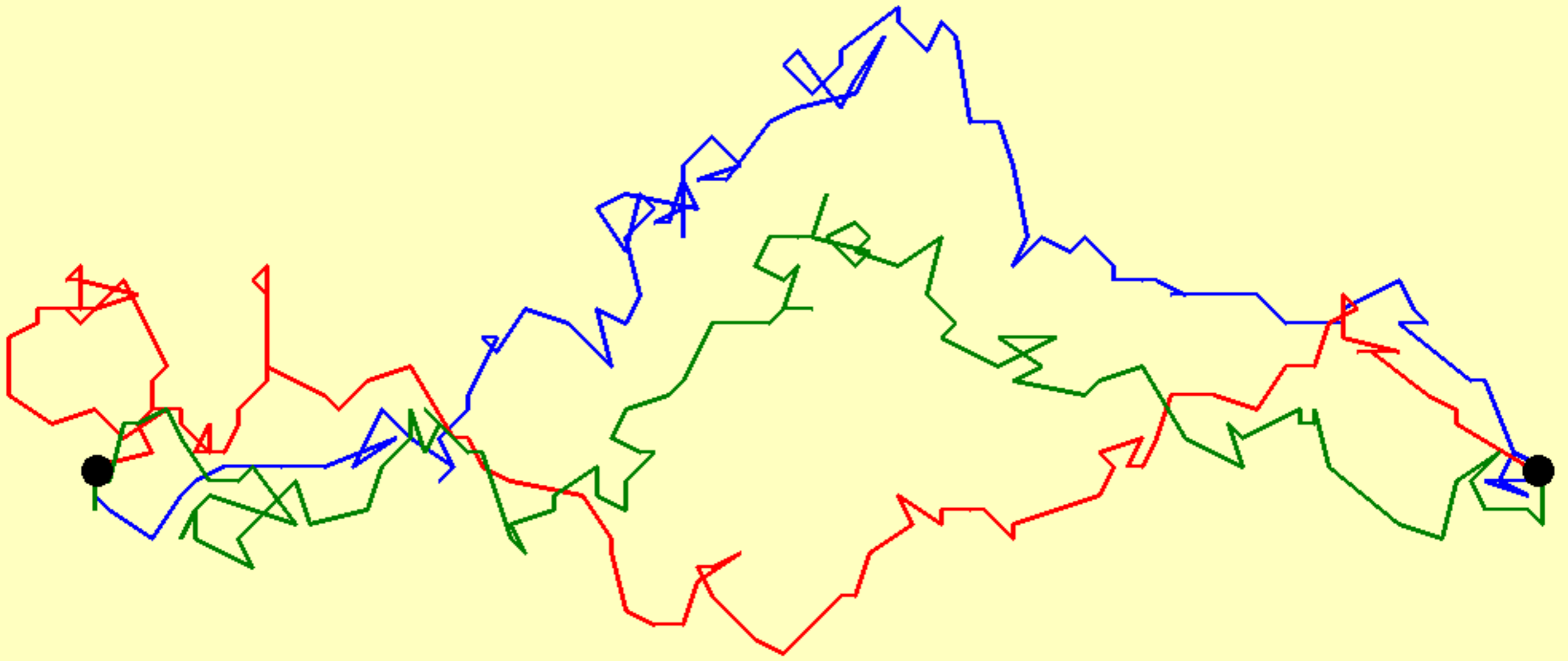
$$h^2(m) = h_{loc}^2 + 2m/n(1 - m/n)DT \quad n = 4$$



$$u(\mathbf{z}) = \frac{1}{2\pi N} \sum_{i=1}^N \frac{1}{h_i^2} \exp \left[-\frac{\|\mathbf{z}_i - \mathbf{z}\|^2}{2h_i^2} \right]$$







COMPUTATION OF CONDITIONAL PROBABILITIES

$$\text{Proba}(\mathbf{z}_t | \mathbf{z}_0, \mathbf{z}_T) = \frac{\text{Proba}(\mathbf{z}_t | \mathbf{z}_0) \times \text{Proba}(\mathbf{z}_T | \mathbf{z}_0, \mathbf{z}_t)}{\text{Proba}(\mathbf{z}_T | \mathbf{z}_0)}$$

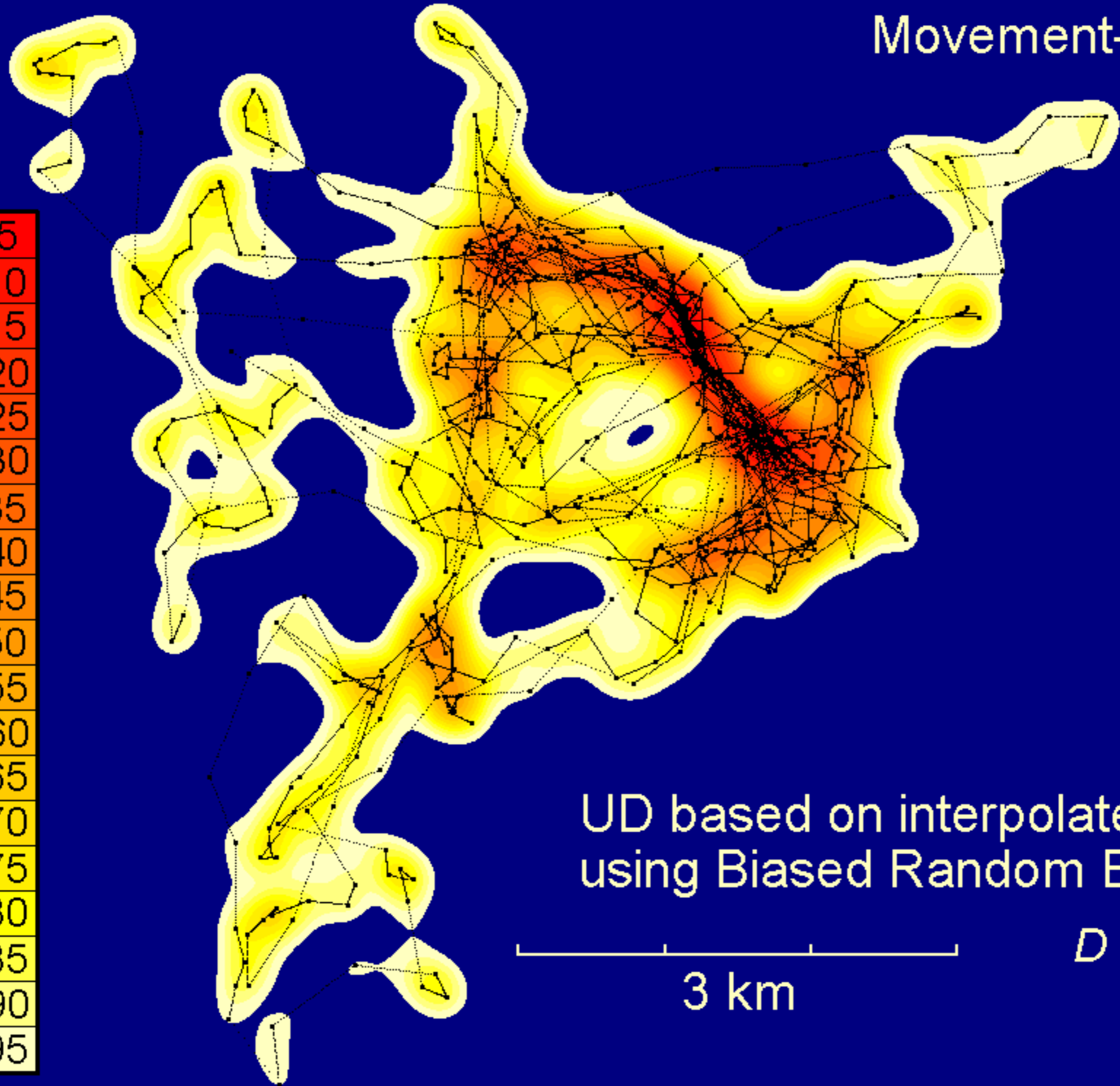
$$\text{Proba}(\mathbf{z}_t | \mathbf{z}_0) = f_W(\mathbf{z}, t | \mathbf{z}_0) \sim \mathcal{N}(\mathbf{z}_0 + \mathbf{v}t, 2\mathbf{D}_{\mathbf{xy}}t)$$

$$\text{Proba}(\mathbf{z}_T | \mathbf{z}_0) = f_W(\mathbf{z}_T, T | \mathbf{z}_0) \sim \mathcal{N}(\mathbf{z}_0 + \mathbf{v}T, 2\mathbf{D}_{\mathbf{xy}}T)$$

$$\text{Proba}(\mathbf{z}_T | \mathbf{z}_0, \mathbf{z}_t) = f_W(\mathbf{z}_T, T-t | \mathbf{z}) \sim \mathcal{N}(\mathbf{z} + \mathbf{v}(T-t), 2\mathbf{D}_{\mathbf{xy}}(T-t))$$

$$\text{Proba}(\mathbf{z}_t | \mathbf{z}_0, \mathbf{z}_T) = f_B(\mathbf{z}, t | \mathbf{z}_0, \mathbf{z}_T) \sim \mathcal{N}(\mathbf{z}_0 + (\mathbf{z}_T - \mathbf{z}_0)t/T, 2\mathbf{D}_{\mathbf{xy}}t(1-t/T))$$

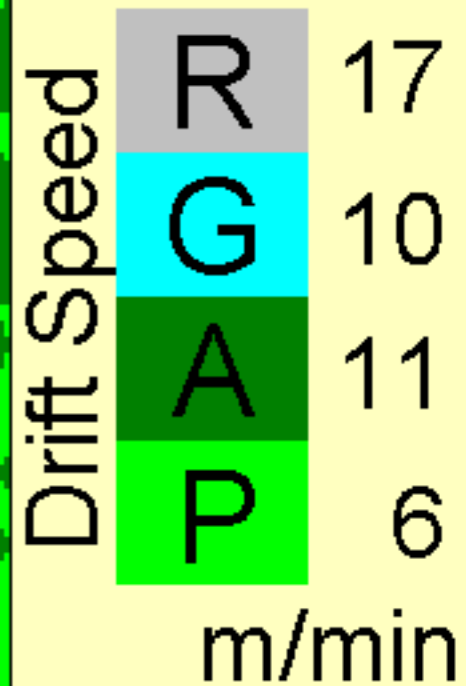
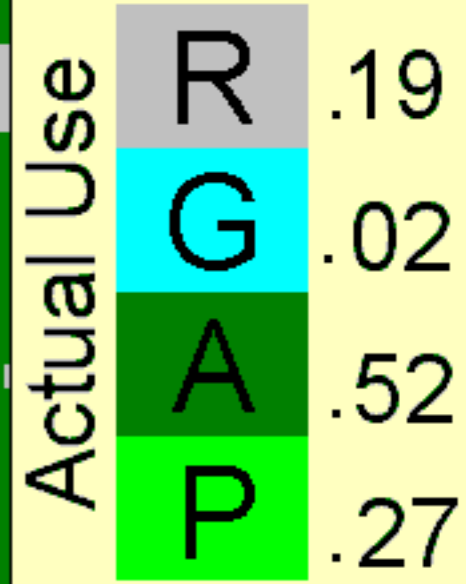
Movement-based KDE



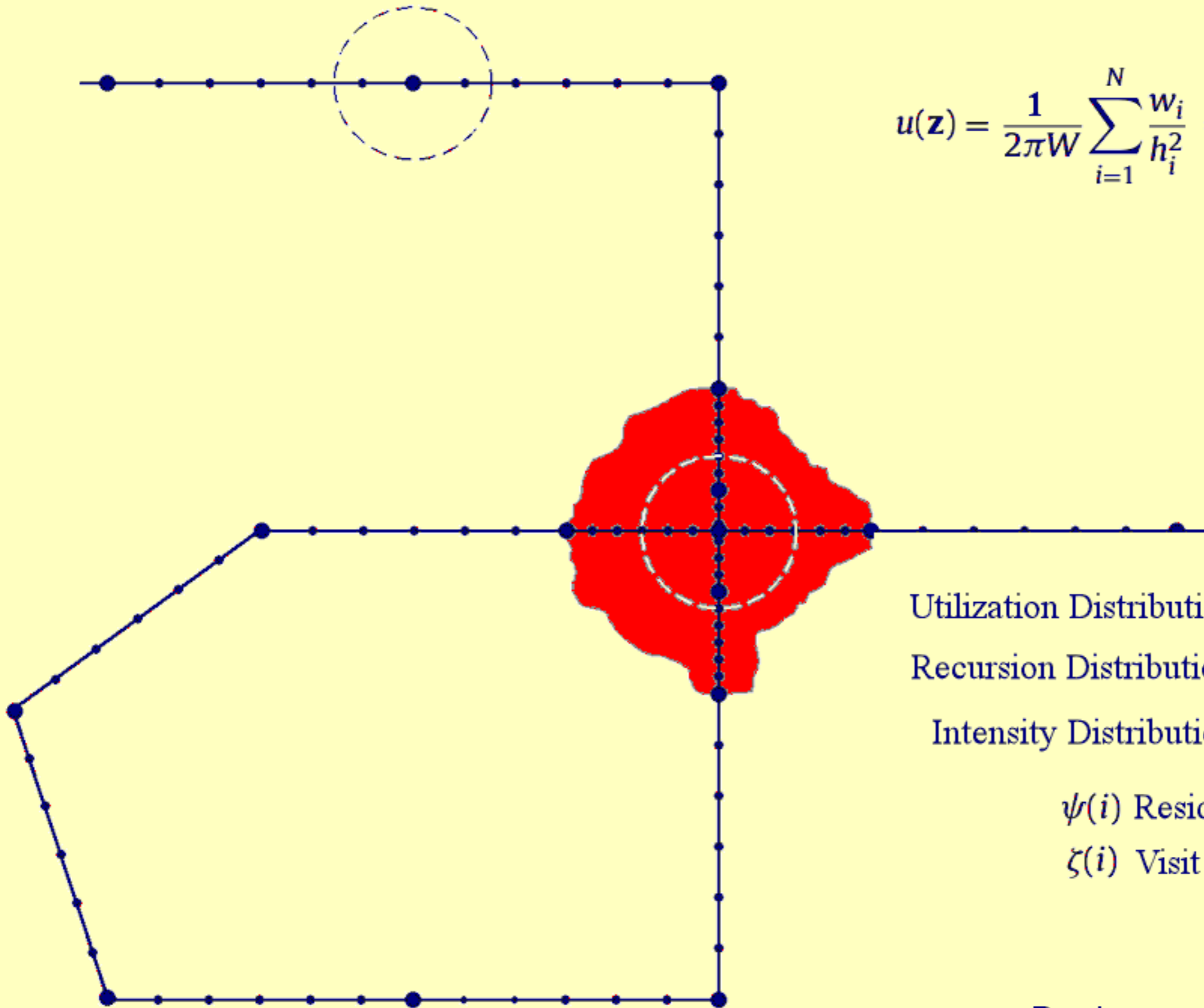
UD based on interpolated locations using Biased Random Bridges



$D = 450 \text{ m}^2/\text{min}$



3 km



$$u(\mathbf{z}) = \frac{1}{2\pi W} \sum_{i=1}^N \frac{w_i}{h_i^2} \exp \left[-\frac{\|\mathbf{z}_i - \mathbf{z}\|^2}{2h_i^2} \right]$$

$$\text{with } W = \sum_{i=1}^N w_i$$

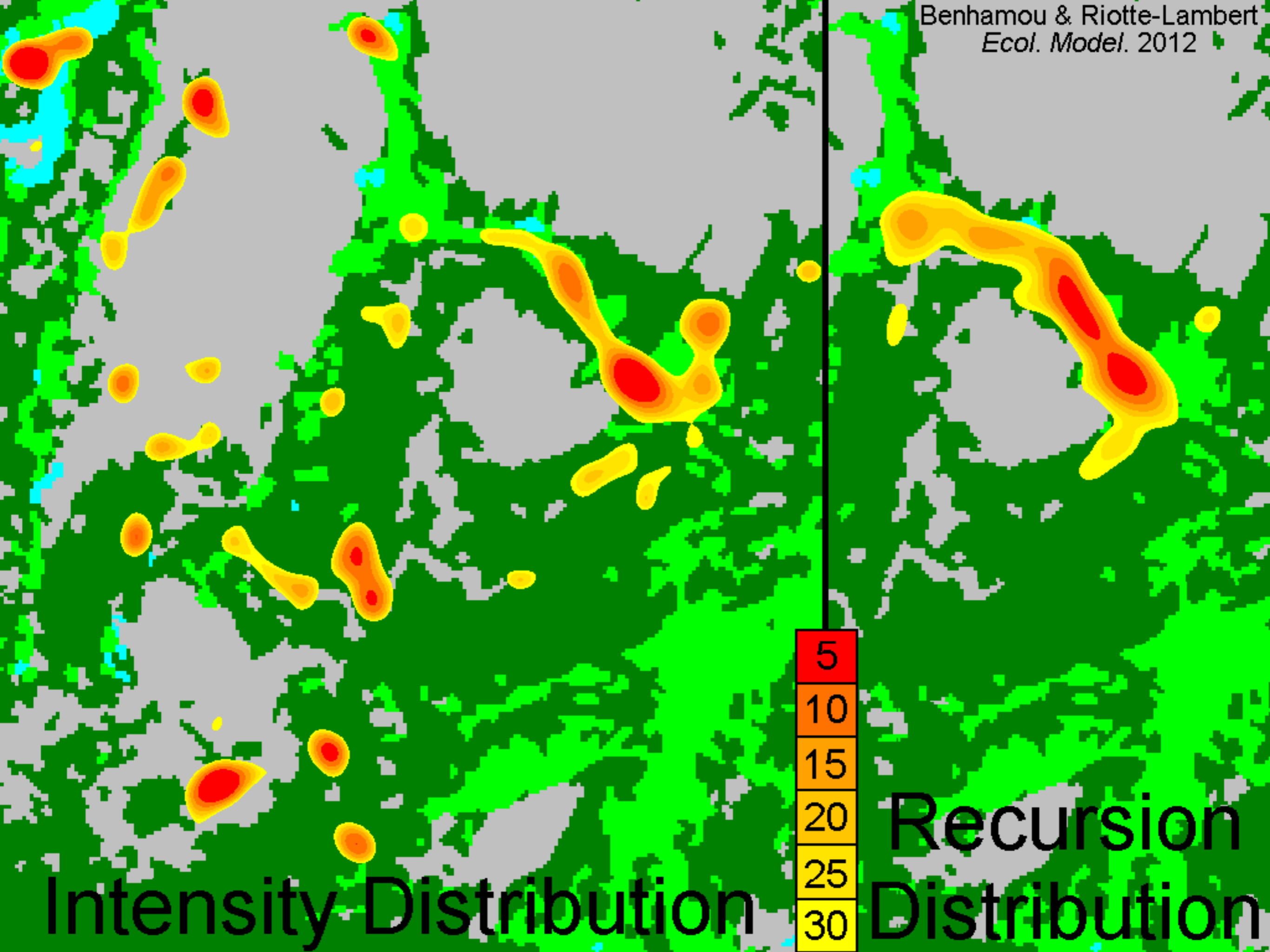
Utilization Distribution UD $w_i = 1$

Recursion Distribution RD $w_i = 1/\psi(i)$

Intensity Distribution ID $w_i = 1/\zeta(i)$

$\psi(i)$ Residence time

$\zeta(i)$ Visit number



Intensity Distribution

Recursion
Distribution

Encounter "probability" of two animals moving independently of each other

What does mean "encounter"?

- to be in the same area
- to be within a given distance of the other one

There are four situations that are worth considering:

- 1) At a given time and at a given place (in the same area)
- 2) At any time and at a given place (in the same area)
- 3) At a given time at any place (within a given distance)
- 4) At any time and at any place (within a given distance)

1) At a given time and at a given place (in the same area)

Consider a circular area Z with centre C and radius R ,
and 2 animals A and B

Encounter Prob. = $P(A \text{ is in } Z \text{ at time } t) \times P(B \text{ is in } Z \text{ at time } t)$

Let the locations of A and B at any time t follow a circular bivariate Gaussian distribution with means $\mu_A(t)$ and $\mu_B(t)$ and standard deviations $\sigma_A(t)$ and $\sigma_B(t)$.

Let C be at distances $\lambda_A(t)$ of $\mu_A(t)$ and $\lambda_B(t)$ of $\mu_B(t)$

The probability density for an animal to be at distance δ of C is given by the Rice distribution: $f(\delta) = \delta/\sigma^2 \exp[-(\delta^2 + \lambda^2)/(2\sigma^2)] \mathbf{I}_0(\lambda\delta/\sigma^2)$
where \mathbf{I}_0 is the modified Bessel function of the first kind with order zero

Probability to be in Z : $F(R) = \int_0^R f(\delta) d\delta$ (using numerical integration)

(if Z is not circular, the prob. can be estimated by computer simulations)

2) At any time and at a given place (in the same area)

Consider an area Z of any shape (not necessarily circular)

Time integration of movement to compute the UD_s of the two animals
=> computation of the proportion of time spent by each animal in area Z

Encounter "prob." = P_{Ption} of time (A in Z) x P_{Ption} of time (B in Z)

3) At a given time at any place (within a given distance D)

Let the locations of A and B at any time t follow a circular bivariate Gaussian distribution with means $\mu_A(t)$ and $\mu_B(t)$ and variances $\sigma_A^2(t)$ and $\sigma_B^2(t)$.

=> the difference follows a circular bivariate Gaussian distribution with mean $\mu_\Delta(t) = \mu_A(t) - \mu_B(t)$ and variance $\sigma_\Delta^2(t) = \sigma_A^2(t) + \sigma_B^2(t)$

The probability density for an animal to be at distance δ of another animal at time t is given by the Rice distribution:

$$f(\delta) = \delta / \sigma_\Delta^2 \exp[-(\delta^2 + \|\mu_\Delta\|^2) / (2\sigma_\Delta^2)] \mathbf{I}_0(\|\mu_\Delta\| \delta / \sigma_\Delta^2)$$

Probability to be within D of each other:

$$F(D) = \int_0^D f(\delta) d\delta \quad (\text{by numerical integration})$$

4) At any time and at any place (within a given distance D)

Compute the "difference distribution" at any time, as previously:

=> Circular bivariate Gaussian distribution

with mean $\mu_{\Delta}(t)$ and variance $\sigma_{\Delta}^2(t)$

Integrate over time (e.g. using kernel approach) => "difference UD"

Then, compute the proportion of time spent in a circular area centred on $(0, 0)$ with radius D

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- 5) JOINT SPATIAL DISTRIBUTION OF 2 (OR MORE) INDIVIDUALS OPENS
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THAT'S

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FOLKS

...thanks