

## Lecture 10: FTLEs for the baker's map

Recall the (generalized) baker's map:

$$X = (x, y) \in [0, 1]^2. \quad X_{n+1} = \varphi(X_n)$$

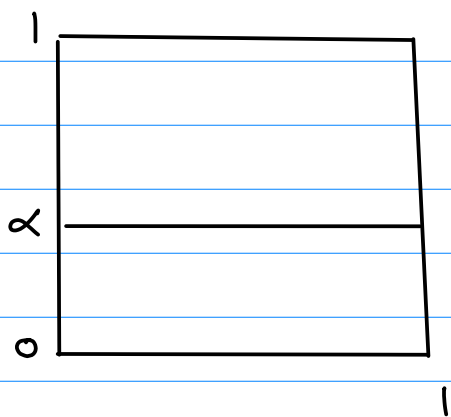
$$x_{n+1} = \begin{cases} \alpha x_n & y_n < \alpha \\ \alpha + \beta x_n & y_n > \alpha \end{cases} \quad \alpha + \beta = 1$$

$$y_{n+1} = \begin{cases} \alpha^{-1} y_n & y_n < \alpha \\ \beta^{-1} (y_n - \alpha) & y_n > \alpha \end{cases}$$

We computed Lyapunov exponents

$$\lambda^{(2)} = -\lambda^{(1)} = \lambda = \alpha \log \alpha^{-1} + \beta \log \beta^{-1}$$

We used Birkhoff's ergodic thm, which suggest iterates land in lower box with probability  $\alpha$ , upper box w. prob  $\beta$ .



Suggests writing

$$\lambda_n = \frac{1}{n} \sum_{k=1}^n h_k$$

where  $h_k = \log \alpha^{-1}$  w. prob  $\alpha$

$\log \beta^{-1}$  w. prob  $\beta$

are i.i.d.

If  $n \rightarrow \infty$  the law of large numbers says  $\lambda_n \rightarrow \lambda$ .

What about for finite  $n$ ? What is the PDF of  $\lambda_n$ ?  
(prob. dist. func.)

This is a standard problem in probability.

For small deviations the central limit theorem holds, but we'll be interested in large deviations:

$$\mathbb{P}\left\{|\lambda_n - \lambda| < \frac{c}{\sqrt{n}}\right\} \quad \text{vs} \quad \mathbb{P}\left\{|\lambda_n - \lambda| < c\right\}$$

*small deviations*                      *large deviations*

$$\langle h \rangle = \lambda = \alpha \log \alpha^{-1} + \beta \log \beta^{-1}$$

$$\sigma^2 = \langle (h - \lambda)^2 \rangle = \alpha (\log \alpha^{-1} - \lambda)^2 + \beta (\log \beta^{-1} - \lambda)^2$$

$$= \alpha \left( \underbrace{(1-\alpha)}_{\beta} \log \alpha^{-1} - \beta \log \beta^{-1} \right)^2 + \beta \left( \underbrace{(1-\beta)}_{\alpha} \log \beta^{-1} - \alpha \log \alpha^{-1} \right)^2$$

$$= \alpha \beta^2 \left( \log (\alpha^{-1} / \beta^{-1}) \right)^2 + \beta \alpha^2 \left( \log (\beta^{-1} / \alpha^{-1}) \right)^2$$

$$= \alpha \beta (\alpha + \beta) \log^2 (\alpha / \beta)$$

$$\sigma^2 = \alpha \beta \log^2 (\alpha / \beta)$$

To find the distribution of  $\lambda_n$ , first find the generating function for  $h$ :

$$\langle e^{hs} \rangle = \alpha e^{s \log \alpha^{-1}} + \beta e^{s \log \beta^{-1}}$$

The generating function for  $\lambda_n$  is:

$$\begin{aligned} \langle e^{\lambda_n s} \rangle &= \langle e^{\frac{s}{n} \sum h_n} \rangle \\ &= \langle \prod e^{\frac{s}{n} h_n} \rangle \\ &= \left\langle e^{\frac{s}{n} h} \right\rangle^n \quad \text{since } h_n \text{ are i.i.d.} \\ &= \left( \alpha e^{\frac{s}{n} \log \alpha^{-1}} + \beta e^{\frac{s}{n} \log \beta^{-1}} \right)^n \\ &= e^{n \Lambda(s/n)} \\ &= e \end{aligned}$$

where

$$\Lambda(s) = \log \left( \alpha e^{s \log \alpha^{-1}} + \beta e^{s \log \beta^{-1}} \right)$$

We want to invert the two-sided Laplace transform to obtain the prob. density function of  $\lambda_n$ , for large  $n$ .

Cramér's theorem then tells us we need to find:

$$I(x) = \sup_s \{ x s - \Lambda(s) \}$$

Assume  $0 < \alpha < 1/2$ , so  $\alpha < \beta$  and  $\log \alpha^{-1} > \log \beta^{-1}$ .

$$\Lambda(s) = s \log \beta^{-1} + \log (\alpha e^{s(\log \alpha^{-1} - \log \beta^{-1})} + \beta)$$

We can find  $I(x)$  using calculus:

$$\begin{aligned} \frac{d}{ds} (xs - \Lambda(s)) &= x - \Lambda'(s) \\ &= x - \log \beta^{-1} - \frac{\alpha (\log \alpha^{-1} - \log \beta^{-1}) e^{(\log \alpha^{-1} - \log \beta^{-1})s}}{\alpha e^{s(\log \alpha^{-1} - \log \beta^{-1})} + \beta} \\ &= 0 \end{aligned}$$

Solve for  $s = s_x(x)$ !

$$s_x(x) = \frac{\log \left( \frac{\beta(x - \log \beta^{-1})}{\alpha(\log \alpha^{-1} - x)} \right)}{\log \alpha^{-1} - \log \beta^{-1}}, \quad \log \beta^{-1} < x < \log \alpha^{-1}.$$

Hence,

$$I(x) = \log \left( \frac{\log \alpha^{-1} - x}{\beta(\log \alpha^{-1} - \log \beta^{-1})} \right) + \left( \frac{x - \log \beta^{-1}}{\log \alpha^{-1} - \log \beta^{-1}} \right) \log \left( \frac{\beta(x - \log \beta^{-1})}{\alpha(\log \alpha^{-1} - x)} \right)$$

This is the rate function (or Cramér function, or entropy function)

Note that  $I(x)$  has a minimum at  $x = \lambda$ ,  
and that  $I''(\lambda) = 1/\sigma^2$

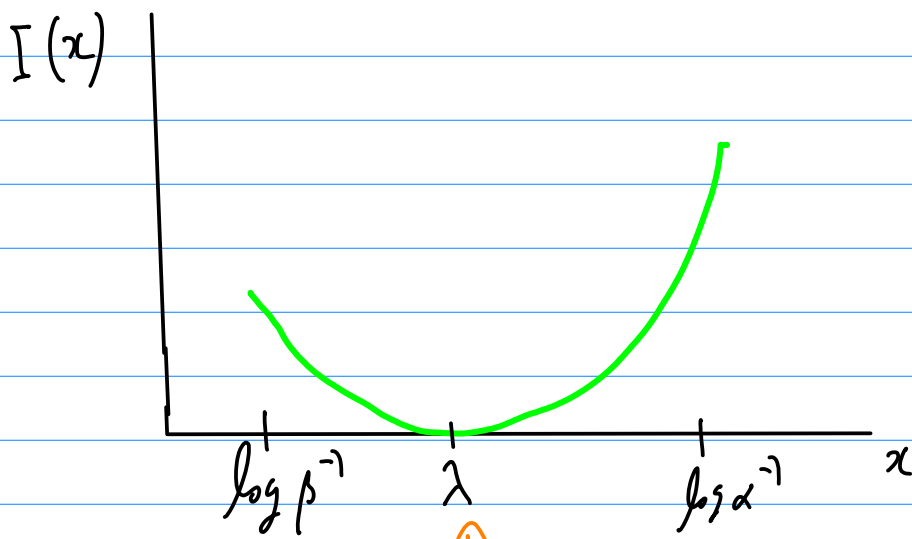
We have finally that

$$p_{\lambda_n}(h) \sim \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-n I(h))$$

$n \rightarrow \infty$

$$\log \beta^{-1} < h < \log \alpha^{-1}$$

Sketch for  $\alpha = 1/4$ ,  $\beta = 3/4$ :



$$I(x) \sim \frac{(x-\lambda)^2}{2\sigma^2}$$

Gaussian approximation

This is normalized properly, since for large  $n$ :

$$\int_{\log \beta^{-1}}^{\log \alpha^{-1}} p_{\lambda_n}(h) dh \sim \int_{-\infty}^{\infty} \frac{\sqrt{n}}{\sqrt{2\pi n^2}} \exp\left(-n \frac{I''(\lambda)(h-\lambda)^2}{2}\right) dh$$

$n \rightarrow \infty$

$$= 1 \quad (+ \text{exponentially small terms})$$

This PDF matches simulations very well.

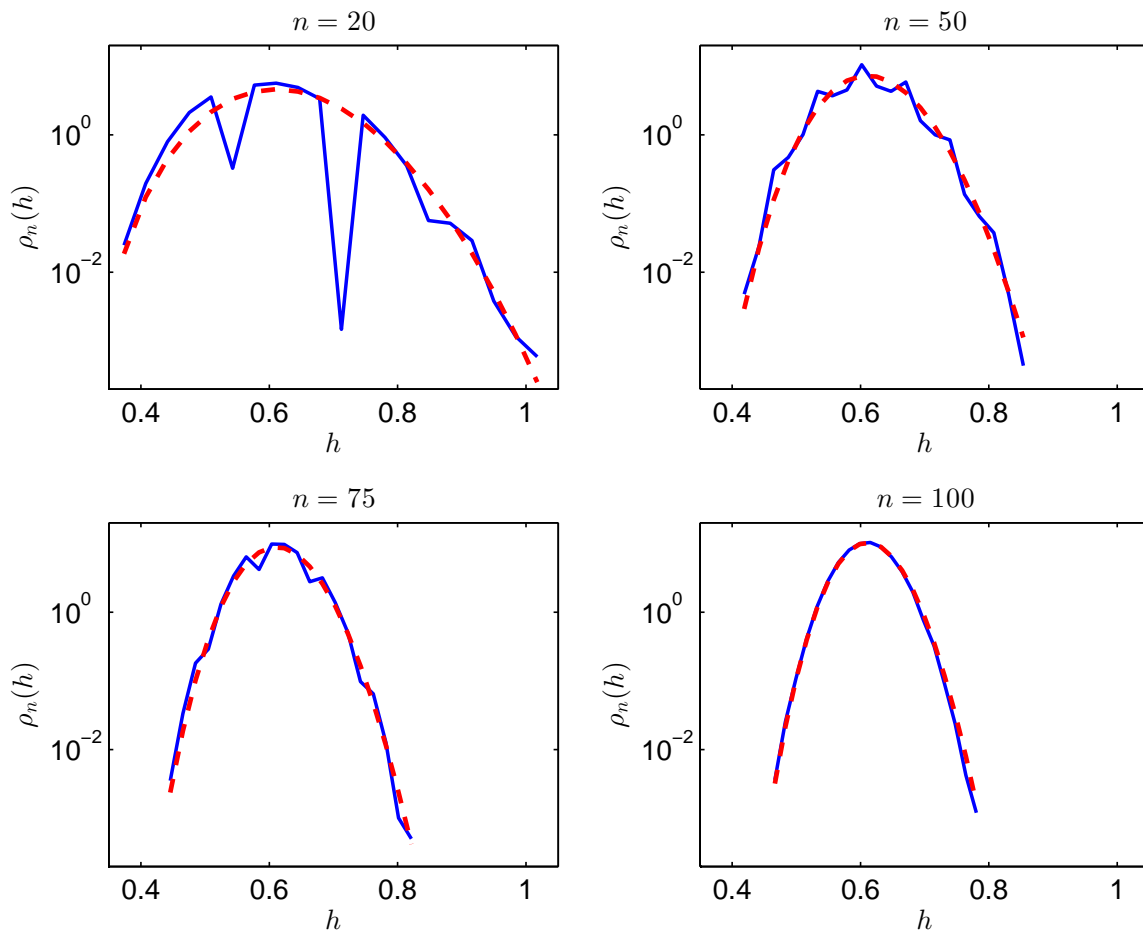


Figure 1: The probability distribution of finite-time Lyapunov exponents for the baker's map with  $\alpha = 0.3$ . As the iterate  $n$  increases, the distribution converges to the large-deviation probability density,  $\rho_n(h)$  (dashed red). The distribution was computed using  $10^5$  randomly-distributed trajectories. See Figs. 2 and 3 for the Matlab code used to generate these figures.

```

function dist_baker

Npts = 100000; Niter = 100; % number of initial points and iterates
alpha = .3; beta = 1-alpha;

% The large-deviation form of the PDF.
mh = @(h) (h + log(beta))/(log(beta/alpha));
G = @(h) mh(h).*log(mh(h)) + (1-mh(h)).*log(1-mh(h)) ...
    + mh(h)*log(beta/alpha) - log(beta);
sigma2 = alpha*beta*log(alpha/beta)^2;
Pld = @(h,n) sqrt(n/2/pi/sigma2) * exp(-n*G(h));

% Specify which 4 values of iterate n to plot.
plotn = [20 50 75 100]; plotgeom = [2 2]; nplot = 0;
% Generate random initial conditions.
rng('default'); X = rand(Npts,2);
lstr = zeros(Npts,1); % the log-stretch
for n = 1:Niter
    [X,str] = baker(X,alpha); % apply baker's map (vectorized)
    lstr = lstr + log(str);
    if any(plotn == n)
        % Plot the results.
        nplot = nplot + 1; subplot(plotgeom(1),plotgeom(2),nplot)
        % Histogram of average stretching, normalized.
        [P,bins] = hist(lstr/n,20); P = P/trapz(bins,P);
        semilogy(bins,P,'b','LineWidth',1.5), hold on
        semilogy(bins,Pld(bins,n),'r--','LineWidth',2), hold off
        xlabel('$h$', 'Interpreter', 'LaTeX')
        ylabel('$\rho_{n}(h)$', 'Interpreter', 'LaTeX')
        axis([.35 1.05 2e-4 2e1])
        title(sprintf('$n = %d$',n), 'Interpreter', 'LaTeX')
    end
end
print -dpdf dist_baker.pdf

```

Figure 2: The Matlab code `dist_baker.m`.



```

function [Xn,stretch] = baker(X,al)
%BAKER Baker's map.
% XN = BAKER(X) returns the image of X=(x,y) under the action of the
% baker's map. BAKER(X,ALPHA) returns the generalized baker's map, where
% 0 < ALPHA < 1. X must be in the unit square [0,1]^2. X can also be an
% array with a 2-vector on each row.
%
% [XN,STRETCH] = BAKER(X) returns a vector STRETCH that records the
% vertical stretching experienced by the particle (1/alpha or
% 1/(1-alpha)). This is used to reconstruct the tangent map.

if nargin < 2
    % Default is the uniform baker's map.
    al = 0.5;
end

if al > 1 || al < 0
    error('Baker's map requires 0 < alpha < 1.')
end

be = 1-al;
x = X(:,1); y = X(:,2);
xn = zeros(size(x)); yn = zeros(size(y)); % Allocate arrays.

% Formula for y <= alpha.
ila = find(y <= al);
xn(ila) = al*x(ila);
yn(ila) = y(ila)/al;
% Formula for y > alpha.
iga = find(y > al);
xn(iga) = al + be*x(iga);
yn(iga) = (y(iga) - al)/be;

Xn = [xn yn];

if nargin > 1
    stretch = 1/al*ones(size(xn));
    stretch(iga) = 1/be;
end

```

Figure 3: The Matlab code `baker.m`.