

# State-dependent Foster-Lyapunov criteria

Stephen Connor

[stephen.connor@york.ac.uk](mailto:stephen.connor@york.ac.uk)

Joint work with Gersende Fort, CNRS-TELECOM ParisTech;  
supported by CRiSM and the French National Research Agency

THE UNIVERSITY *of York*

March 2012

# Outline

- 1 Introduction
  - The general problem
  - Drift conditions
- 2 Establishing a subsampled drift condition
  - Examples
- 3 Using a subsampled drift condition
  - Interplay of subsampling rates and moments
- 4 Applications

# The general problem

Let  $\Phi = \{\Phi_n, n \geq 0\}$  be a time-homogeneous Markov chain on a state space  $X$ . (Assume that  $\Phi$  is  $\phi$ -irreducible and aperiodic, for simplicity.)

We're interested in what can be said about the long-term behaviour of  $\Phi$ . For example:

- does  $\Phi$  converge to an equilibrium distribution?
- if so, in what norm does this convergence take place, and how fast?
- and how is this related to the average time spent between successive visits to certain sets?

# Notation

- $P^n$ :  $n$ -step transition kernel of  $\Phi$ ;
- for a non-negative function  $f$ , and measure  $\mu$ :

$$P^n f(x) = \mathbb{E}_x[f(\Phi_n)], \quad \mu(f) = \int f(y)\mu(dy);$$

- norm  $\|\mu\|_g$ :

$$\|\mu\|_g = \sup_{f:|f|\leq g} |\mu(f)|, \quad \|\cdot\|_{\text{TV}} \equiv \|\cdot\|_1;$$

- first return time to a set:  $\tau_{\mathcal{A}} = \inf\{n \geq 1 : \Phi_n \in \mathcal{A}\}$ ;
- $\mathcal{C}$  is a *small set* if  $\exists \varepsilon > 0$  and a measure  $\nu$  s.t.

$$P(x, \cdot) \geq \varepsilon \nu(\cdot) \text{ for all } x \in \mathcal{C}.$$

# Notation

- $P^n$ :  $n$ -step transition kernel of  $\Phi$ ;
- for a non-negative function  $f$ , and measure  $\mu$ :

$$P^n f(x) = \mathbb{E}_x[f(\Phi_n)], \quad \mu(f) = \int f(y)\mu(dy);$$

- norm  $\|\mu\|_g$ :

$$\|\mu\|_g = \sup_{f:|f|\leq g} |\mu(f)|, \quad \|\cdot\|_{\text{TV}} \equiv \|\cdot\|_1;$$

- first return time to a set:  $\tau_{\mathcal{A}} = \inf\{n \geq 1 : \Phi_n \in \mathcal{A}\}$ ;
- $\mathcal{C}$  is a *small set* if  $\exists \varepsilon > 0$  and a measure  $\nu$  s.t.

$$P(x, \cdot) \geq \varepsilon \nu(\cdot) \text{ for all } x \in \mathcal{C}.$$

# Notation

- $P^n$ :  $n$ -step transition kernel of  $\Phi$ ;
- for a non-negative function  $f$ , and measure  $\mu$ :

$$P^n f(x) = \mathbb{E}_x[f(\Phi_n)], \quad \mu(f) = \int f(y)\mu(dy);$$

- norm  $\|\mu\|_g$ :

$$\|\mu\|_g = \sup_{f:|f|\leq g} |\mu(f)|, \quad \|\cdot\|_{\text{TV}} \equiv \|\cdot\|_1;$$

- first return time to a set:  $\tau_{\mathcal{A}} = \inf\{n \geq 1 : \Phi_n \in \mathcal{A}\}$ ;
- $\mathcal{C}$  is a *small set* if  $\exists \varepsilon > 0$  and a measure  $\nu$  s.t.

$$P(x, \cdot) \geq \varepsilon \nu(\cdot) \text{ for all } x \in \mathcal{C}.$$

# Notation

- $P^n$ :  $n$ -step transition kernel of  $\Phi$ ;
- for a non-negative function  $f$ , and measure  $\mu$ :

$$P^n f(x) = \mathbb{E}_x[f(\Phi_n)], \quad \mu(f) = \int f(y)\mu(dy);$$

- norm  $\|\mu\|_g$ :

$$\|\mu\|_g = \sup_{f:|f|\leq g} |\mu(f)|, \quad \|\cdot\|_{\text{TV}} \equiv \|\cdot\|_1;$$

- first return time to a set:  $\tau_{\mathcal{A}} = \inf\{n \geq 1 : \Phi_n \in \mathcal{A}\}$ ;
- $\mathcal{C}$  is a *small set* if  $\exists \varepsilon > 0$  and a measure  $\nu$  s.t.

$$P(x, \cdot) \geq \varepsilon \nu(\cdot) \text{ for all } x \in \mathcal{C}.$$

# Notation

- $P^n$ :  $n$ -step transition kernel of  $\Phi$ ;
- for a non-negative function  $f$ , and measure  $\mu$ :

$$P^n f(x) = \mathbb{E}_x[f(\Phi_n)], \quad \mu(f) = \int f(y)\mu(dy);$$

- norm  $\|\mu\|_g$ :

$$\|\mu\|_g = \sup_{f:|f|\leq g} |\mu(f)|, \quad \|\cdot\|_{\text{TV}} \equiv \|\cdot\|_1;$$

- first return time to a set:  $\tau_{\mathcal{A}} = \inf\{n \geq 1 : \Phi_n \in \mathcal{A}\}$ ;
- $\mathcal{C}$  is a *small set* if  $\exists \varepsilon > 0$  and a measure  $\nu$  s.t.

$$P(x, \cdot) \geq \varepsilon \nu(\cdot) \text{ for all } x \in \mathcal{C}.$$



# Ergodicity

$\Phi$  is called *ergodic* if it has a finite invariant measure  $\pi$  ( $\pi = \pi P$ ).

In this case, for any  $x$ ,

$$\|P^n(x, \cdot) - \pi\|_{\text{TV}} \rightarrow 0 \text{ as } n \rightarrow \infty. \quad (1)$$

Equivalently, we can find a small set  $\mathcal{C}$  with

$$\sup_{x \in \mathcal{C}} \mathbb{E}_x[\tau_{\mathcal{C}}] < \infty.$$

# Ergodicity

$\Phi$  is called *ergodic* if it has a finite invariant measure  $\pi$  ( $\pi = \pi P$ ).

In this case, for any  $x$ ,

$$\|P^n(x, \cdot) - \pi\|_{\text{TV}} \rightarrow 0 \text{ as } n \rightarrow \infty. \quad (1)$$

Equivalently, we can find a small set  $\mathcal{C}$  with

$$\sup_{x \in \mathcal{C}} \mathbb{E}_x[\tau_{\mathcal{C}}] < \infty.$$

But *how fast* does the convergence in (1) take place?

## Definition

$\Phi$  is *geometrically ergodic* if there exists  $r > 1$  with

$$\|P^n(x, \cdot) - \pi(\cdot)\|_{\text{TV}} \leq M_x r^{-n}.$$

## Definition

$\Phi$  is *geometrically ergodic* if there exists  $r > 1$  with

$$\|P^n(x, \cdot) - \pi(\cdot)\|_{\text{TV}} \leq M_x r^{-n}.$$

Equivalently:

- there exists a *scale function*  $V : X \rightarrow [1, \infty)$ , a small set  $\mathcal{C}$ , and constants  $\beta \in (0, 1)$ ,  $b < \infty$ , with

$$\mathbb{E}_x [V(\Phi_1)] = PV(x) \leq \beta V(x) + b \mathbf{1}_{\mathcal{C}}(x);$$

- $\sup_{x \in \mathcal{C}} \mathbb{E}_x [\beta^{-\tau_{\mathcal{C}}}] < \infty.$

# Drift conditions

The inequality

$$PV(x) \leq \beta V(x) + b\mathbf{1}_C(x);$$

is called a *Foster-Lyapunov drift condition*.

- often easiest way of showing that  $\Phi$  is geometrically ergodic;
- if  $V$  is bounded then  $\Phi$  is *uniformly ergodic*.

# Drift conditions

The inequality

$$PV(x) \leq \beta V(x) + b\mathbf{1}_C(x);$$

is called a *Foster-Lyapunov drift condition*.

- often easiest way of showing that  $\Phi$  is geometrically ergodic;
- if  $V$  is bounded then  $\Phi$  is *uniformly ergodic*.

*Subgeometric* ergodicity is implied by a weaker drift condition:

$$PV(x) \leq V(x) - \phi \circ V(x) + b\mathbf{1}_C(x)$$

for some concave non-negative function  $\phi$ .

## Questions:

Drift conditions tend to look at only *one step* of  $\Phi$  though:  
sometimes more convenient to work with a *subsamped chain* . . .

## Questions:

Drift conditions tend to look at only *one step* of  $\Phi$  though:  
sometimes more convenient to work with a *subsamped chain* ...

- 1 When can we find a function  $n : X \rightarrow \mathbb{N}$  such that

$$P^{n(x)} V(x) \leq \beta V(x) + b \mathbf{1}_C(x) ? \quad (2)$$



# Questions:

Drift conditions tend to look at only *one step* of  $\Phi$  though:  
sometimes more convenient to work with a *subsamped chain* ...

- ① When can we find a function  $n : X \rightarrow \mathbb{N}$  such that

$$P^{n(x)} V(x) \leq \beta V(x) + b \mathbf{1}_{\mathcal{C}}(x) \quad (2)$$

- ② Alternatively, if (2) holds for some  $n$  and  $V$ , what can be said about moments of the return time to  $\mathcal{C}$ ?

## Questions:

Drift conditions tend to look at only *one step* of  $\Phi$  though:  
sometimes more convenient to work with a *subsamped chain* ...

- ① When can we find a function  $n : X \rightarrow \mathbb{N}$  such that

$$P^{n(x)}V(x) \leq \beta V(x) + b\mathbf{1}_{\mathcal{C}}(x)? \quad (2)$$

- ② Alternatively, if (2) holds for some  $n$  and  $V$ , what can be said about moments of the return time to  $\mathcal{C}$ ?
- ③ And when is this useful?!

# Establishing a subsampled drift condition

## Theorem (1)

Assume that there exist a small set  $\mathcal{D}$ , a function  $V : X \rightarrow [1, \infty)$  and a continuously differentiable increasing concave function  $\phi : [1, \infty) \rightarrow (0, \infty)$ , such that  $\sup_{\mathcal{D}} V < \infty$ ,  $\inf_{[1, \infty)} \phi > 0$ , and

$$PV \leq V - \phi \circ V + b\mathbf{1}_{\mathcal{D}}.$$

Fix  $\beta \in (0, 1)$  and let  $n : X \rightarrow \mathbb{N}$  satisfy  $n(x) \sim \frac{1}{\beta} \left( \frac{V}{\phi \circ V} \right) (x)$ .

Then for any  $\beta < \beta' < 1$ ,

$$P^{n(x)} W \leq \beta' W + b'\mathbf{1}_{\mathcal{C}},$$

where  $W = \phi \circ V$ .

# Comments

- Theorem (1) says that we can deduce a (state-dependent) subsampled geometric drift condition from a one-step drift, but on a different scale;
- More general results (not requiring a drift condition for  $V$ ) can be stated.

# Examples

$$PV \leq V - \phi \circ V + b\mathbf{1}_D$$

 $\Rightarrow$ 

$$P^{n(x)}W \leq \beta'W + b'\mathbf{1}_C$$

- **Polynomially ergodic:** if  $\phi(t) \sim ct^{1-\alpha}$  for some  $\alpha \in (0, 1)$ , then  $n \sim V^\alpha$  and  $W = V^{1-\alpha}$ .

## Examples

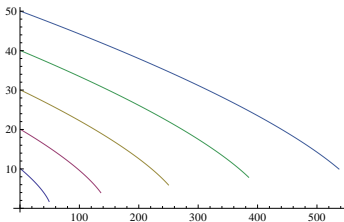
$$PV \leq V - \phi \circ V + b\mathbf{1}_D$$

 $\Rightarrow$ 

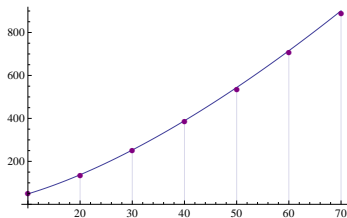
$$P^{n(x)}W \leq \beta'W + b'\mathbf{1}_C$$

- **Polynomially ergodic:** if  $\phi(t) \sim ct^{1-\alpha}$  for some  $\alpha \in (0, 1)$ , then  $n \sim V^\alpha$  and  $W = V^{1-\alpha}$ .

*Motivation:* Deterministic chain:  $\Phi_{n+1} = \Phi_n - \Phi_n^{0.4}$  (so  $V(x) = x$ )



Decay of  $W(\Phi_n) = \Phi_n^{0.4}$



$n : W(\Phi_n) \leq 0.2W(\Phi_0)$   
(blue line  $\propto \Phi_0^{0.6}$ )

# Examples

$$PV \leq V - \phi \circ V + b\mathbf{1}_D$$

 $\Rightarrow$ 

$$P^{n(x)}W \leq \beta'W + b'\mathbf{1}_C$$

- **Polynomially ergodic:** if  $\phi(t) \sim ct^{1-\alpha}$  for some  $\alpha \in (0, 1)$ , then  $n \sim V^\alpha$  and  $W = V^{1-\alpha}$ .
- **Subgeometrically ergodic:** if  $\phi(t) \sim t[\ln t]^{-\alpha}$  for some  $\alpha > 0$ , then  $n \sim [\ln V(x)]^\alpha$  and  $W = V[\ln V]^{-\alpha}$ .

# Examples

$$PV \leq V - \phi \circ V + b\mathbf{1}_D$$

 $\Rightarrow$ 

$$P^{n(x)}W \leq \beta'W + b'\mathbf{1}_C$$

- **Polynomially ergodic:** if  $\phi(t) \sim ct^{1-\alpha}$  for some  $\alpha \in (0, 1)$ , then  $n \sim V^\alpha$  and  $W = V^{1-\alpha}$ .
- **Subgeometrically ergodic:** if  $\phi(t) \sim t[\ln t]^{-\alpha}$  for some  $\alpha > 0$ , then  $n \sim [\ln V(x)]^\alpha$  and  $W = V[\ln V]^{-\alpha}$ .
- **Logarithmically ergodic:** if  $\phi(t) \sim [1 + \ln t]^\alpha$  for some  $\alpha > 0$ , then  $n \sim \frac{V}{[1 + \ln V]^\alpha}$  and  $W = [1 + \ln V]^\alpha$ .



# Using a subsampled drift condition

## Question 2

Suppose we know that

$$P^{n(x)}V(x) \leq \beta V(x) + b\mathbf{1}_C(x).$$

What can be said about moments of  $\tau_C$ ?

# Using a subsampled drift condition

## Question 2

Suppose we know that

$$P^{n(x)}V(x) \leq \beta V(x) + b\mathbf{1}_C(x).$$

What can be said about moments of  $\tau_C$ ?

- If  $n(x) = c$  then  $\Phi$  is geometrically ergodic;

# Using a subsampled drift condition

## Question 2

Suppose we know that

$$P^{n(x)} V(x) \leq \beta V(x) + b \mathbf{1}_C(x).$$

What can be said about moments of  $\tau_C$ ?

- If  $n(x) = c$  then  $\Phi$  is geometrically ergodic;
- Alternative drift condition

$$P^{n(x)} V(x) \leq \beta^{n(x)} V(x) + b \mathbf{1}_C(x)$$

(with no relation assumed between  $n$  and  $V$ ) shown by [Meyn & Tweedie \(1994\)](#) to also imply geometric ergodicity.

## Theorem (2)

Assume that

$$P^{n(x)}V(x) \leq \beta V(x) + b\mathbf{1}_C(x).$$

If there exists a strictly increasing function  $R : (0, \infty) \rightarrow (0, \infty)$  satisfying one of the following conditions

- (i)  $t \mapsto R(t)/t$  is non-increasing and  $R \circ n \leq V$ ,
- (ii)  $R$  is a convex continuously differentiable function such that  $R'$  is log-concave and  $R^{-1}(V) - R^{-1}(\beta V) \geq n$ ,

then there exists a constant  $M$  such that

$$\mathbb{E}_x[R(\tau_C)] \leq M(V(x) + b\mathbf{1}_C(x)).$$

- If  $n(x) \leq V(x)$  then taking  $R(t) = t$  in (i) we obtain

$$\sup_{x \in \mathcal{C}} \mathbb{E}_x[\tau_{\mathcal{C}}] < \infty;$$

- If  $n(x) \leq V(x)$  then taking  $R(t) = t$  in (i) we obtain

$$\sup_{x \in \mathcal{C}} \mathbb{E}_x[\tau_{\mathcal{C}}] < \infty;$$

- Part (i) can be applied when  $V = \xi \circ n$  for some increasing concave function  $\xi$  (i.e. useful when  $n \gg V$ );

- If  $n(x) \leq V(x)$  then taking  $R(t) = t$  in (i) we obtain

$$\sup_{x \in \mathcal{C}} \mathbb{E}_x[\tau_{\mathcal{C}}] < \infty;$$

- Part (i) can be applied when  $V = \xi \circ n$  for some increasing concave function  $\xi$  (i.e. useful when  $n \gg V$ );
- Alternatively, if  $n = \xi \circ V$  then

$$R^{-1}(t) \sim \int_1^t \frac{\xi(u)}{u} du$$

satisfies (ii) (i.e. this is useful when  $n/V$  decreasing).

# Interplay of subsampling rates and moments

**Geometric rates:** if  $n(x) = 1$ , take  $R(t) = \kappa^t$ , with  $1 \leq \kappa \leq \beta^{-1}$ .

Then

- $R$  is convex and log-concave;
- $R^{-1}(V) - R^{-1}(\beta V) = (\ln \beta^{-1})/(\ln \kappa) \geq 1 = n$ .

Thus (ii) shows that

$$\mathbb{E}_x [R(\tau_c)] = \mathbb{E}_x [\kappa^{\tau_c}] \leq M(V(x) + b\mathbf{1}_c(x)) ,$$

and so  $\mathbb{E}_x [\beta^{-\tau_c}] < \infty$ .



# Interplay of subsampling rates and moments

**Polynomial rates:** suppose  $n(x) \sim V^{\frac{\alpha}{(1-\alpha)}}(x)$ , for some  $\alpha \in (0, 1]$ .  
Letting  $R(t) \sim t^{1/\alpha-1}$ , we see that

- when  $\alpha \leq 1/2$  then  $R$  satisfies (ii);
- when  $\alpha \geq 1/2$  then  $R(t)/t$  is non-increasing, and

$$R \circ n \sim (V^{\frac{\alpha}{(1-\alpha)}})^{1/\alpha-1} = V,$$

and so  $R$  satisfies (i).

## Interplay of subsampling rates and moments

**Polynomial rates:** suppose  $n(x) \sim V^{\frac{\alpha}{(1-\alpha)}}(x)$ , for some  $\alpha \in (0, 1]$ .  
Letting  $R(t) \sim t^{1/\alpha-1}$ , we see that

- when  $\alpha \leq 1/2$  then  $R$  satisfies (ii);
- when  $\alpha \geq 1/2$  then  $R(t)/t$  is non-increasing, and

$$R \circ n \sim (V^{\frac{\alpha}{(1-\alpha)}})^{1/\alpha-1} = V,$$

and so  $R$  satisfies (i).

In either case, we obtain

$$\mathbb{E}_x \left[ \tau_c^{1/\alpha-1} \right] \leq cV(x).$$

**Logarithmic** and **subgeometric** rates can be dealt with similarly.

## Corollary (to Theorem (2))

*If  $\pi(V) < \infty$  then there exists a small set  $\mathcal{D}$  with*

$$\sup_{x \in \mathcal{D}} \mathbb{E}_x \left[ \sum_{k=0}^{\tau_{\mathcal{D}}} R(k) \right] < \infty.$$

### Corollary (to Theorem (2))

If  $\pi(V) < \infty$  then there exists a small set  $\mathcal{D}$  with

$$\sup_{x \in \mathcal{D}} \mathbb{E}_x \left[ \sum_{k=0}^{\tau_{\mathcal{D}}} R(k) \right] < \infty.$$

**Polynomial chains:** if  $PV \leq V - cV^{1-\alpha} + b\mathbf{1}_{\mathcal{C}}$  then (Thm (1))

$$P^{n(x)}W(x) \leq \beta'W(x) + b'\mathbf{1}_{\mathcal{D}},$$

where  $W \sim V^{1-\alpha}$  and  $n \sim V^{\alpha}$ ; furthermore,  $\pi(W) < \infty$ .

### Corollary (to Theorem (2))

If  $\pi(V) < \infty$  then there exists a small set  $\mathcal{D}$  with

$$\sup_{x \in \mathcal{D}} \mathbb{E}_x \left[ \sum_{k=0}^{\tau_{\mathcal{D}}} R(k) \right] < \infty.$$

**Polynomial chains:** if  $PV \leq V - cV^{1-\alpha} + b\mathbf{1}_{\mathcal{C}}$  then (Thm (1))

$$P^{n(x)}W(x) \leq \beta'W(x) + b'\mathbf{1}_{\mathcal{D}},$$

where  $W \sim V^{1-\alpha}$  and  $n \sim V^{\alpha}$ ; furthermore,  $\pi(W) < \infty$ .

Using  $R(t) \sim t^{1/\alpha-1}$  in the **Corollary** we obtain

$$\mathbb{E}_x \left[ \tau_{\mathcal{C}}^{1/\alpha} \right] < \infty.$$

# Application: tame chains

Class of Markov chains introduced by [SBC & Kendall \(2007\)](#).

## Definition

$\Phi$  is *tame* if the following two conditions hold:

- (i) there exist  $\delta \in (0, 1)$  and a deterministic function  $n$  satisfying  $n(x) \leq W^\delta(x)$  such that

$$\mathbb{E}_x [W(\Phi_{n(x)})] \leq \beta W(x) + b \mathbf{1}_C(x);$$

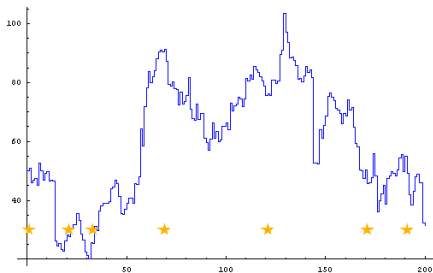
- (ii) the constant  $\delta$  satisfies  $\ln \beta < \delta^{-1} \ln(1 - \delta)$ .

*i.e.*  $\Phi$  satisfies a subsampled geometric drift condition, where the subsampling time  $n$  is not too large.

## Theorem (SBC & Kendall, 2007)

If  $\Phi$  is tame then there exists a perfect simulation algorithm for  $\Phi$  (using Dominated Coupling from the Past).

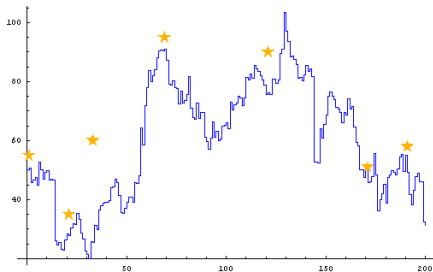
**Idea of proof:** there exists a simple dominating process for any geometrically ergodic chain (Kendall, 2004); *delay* this (using  $n$ ) to produce dominating process for  $X$ .



## Theorem (SBC & Kendall, 2007)

If  $\Phi$  is tame then there exists a perfect simulation algorithm for  $\Phi$  (using Dominated Coupling from the Past).

**Idea of proof:** there exists a simple dominating process for any geometrically ergodic chain (Kendall, 2004); *delay* this (using  $n$ ) to produce dominating process for  $X$ .

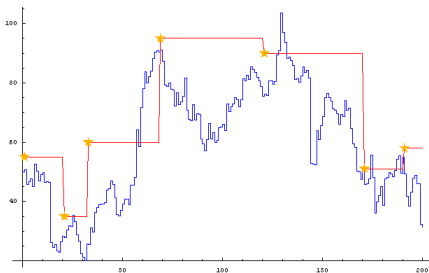




## Theorem (SBC & Kendall, 2007)

*If  $\Phi$  is tame then there exists a perfect simulation algorithm for  $\Phi$  (using Dominated Coupling from the Past).*

**Idea of proof:** there exists a simple dominating process for any geometrically ergodic chain (Kendall, 2004); *delay* this (using  $n$ ) to produce dominating process for  $X$ .



# When is a chain tame?

- All geometrically ergodic chains are tame.

## Proposition

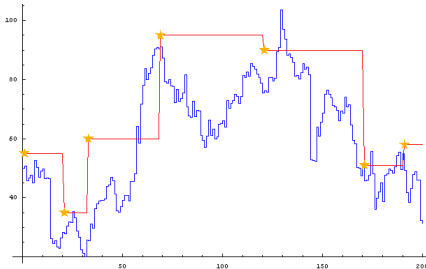
*If  $PV \leq V - cV^{1-\alpha} + b\mathbf{1}_C$ , with  $\alpha \in (0, 1/2)$ , then  $\Phi$  is tame.*

- Proof easy, using Theorem (1).
- Follows that chains with subgeometric drift ( $\phi(t) \sim t[\ln t]^{-\alpha}$ ) are tame.
- Logarithmically ergodic chains ( $\phi(t) \sim [1 + \ln t]^\alpha$ ) not covered by this result.

# Dominating process

Can also use above theory to determine ergodic properties of the dominating process  $D$  for  $\Phi$  in the perfect simulation algorithm.

- $D$  does not satisfy a simple one-step drift condition;
- but establishing state-dependent drift is simple!
- Theorem (2) provides information about ergodic properties of  $D$ .



# Dominating process

Can also use above theory to determine ergodic properties of the dominating process  $D$  for  $\Phi$  in the perfect simulation algorithm.

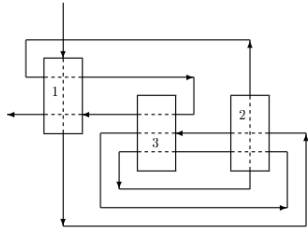
- $D$  does not satisfy a simple one-step drift condition;
- but establishing state-dependent drift is simple!
- Theorem (2) provides information about ergodic properties of  $D$ .

*E.g.* if  $n(x) \sim W(x)^\gamma$  (with  $\gamma \leq \delta$ ), then  $D$  is ergodic and converges to  $\pi_D$  polynomially fast (in total variation)

- but note that this isn't enough to guarantee that the mean run-time of the domCFTP algorithm is finite . . .

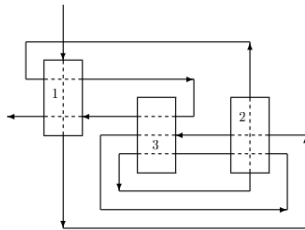
# Other applications/extensions

- Sufficient conditions for ergodicity of strong Markov processes
  - applications in queueing and network stability
  - continuum range of rates of convergence
  - explicit norm of convergence



# Other applications/extensions

- Sufficient conditions for ergodicity of strong Markov processes
  - applications in queueing and network stability
  - continuum range of rates of convergence
  - explicit norm of convergence
- Yüksel & Meyn (2012) use *random-time, state-dependent drift criteria* to prove stability results, but *not* convergence rates ...



# References

Connor, S. B. and G. Fort (2009).

State-dependent FosterLyapunov criteria for subgeometric convergence of Markov chains.

*Stochastic Processes and their Applications* 119(12), 4176–4193.

Connor, S. B. and W. S. Kendall (2007).

Perfect Simulation for a Class of Positive Recurrent Markov Chains.

*Ann. Appl. Probab.* 17, 781–808.

Kendall, W. S. (2004).

Geometric Ergodicity and Perfect Simulation.

*Electron. Comm. Probab.* 9, 140–151.

Meyn, S. P. and R. L. Tweedie (1994).

State-dependent criteria for convergence of Markov chains.

*Ann. Appl. Probab.* 4, 149–168.

Yüksel, S. and S. Meyn (2012).

Random-Time, State-Dependent Stochastic Drift for Markov Chains and Application to Stochastic Stabilization Over Erasure Channels.

*Preprint.*