

Recurrence theorems for topological Markov chains

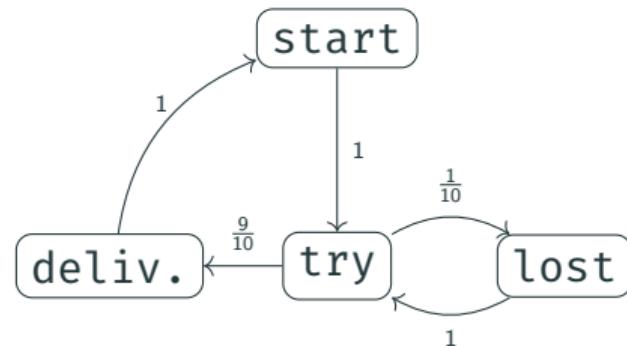
Cédric Ho Thanh, Natsuki Urabe, and Ichiro Hasuo

iTHEMS, April 22nd 2022

Finite Makov chains

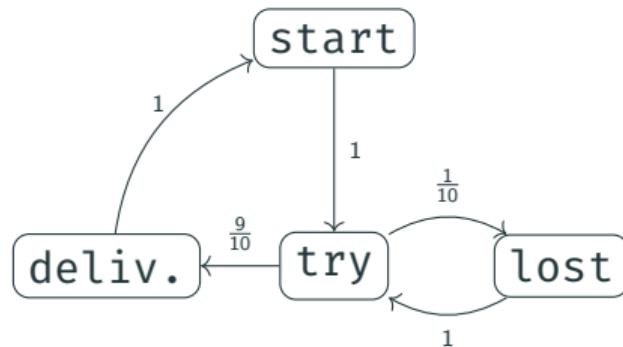
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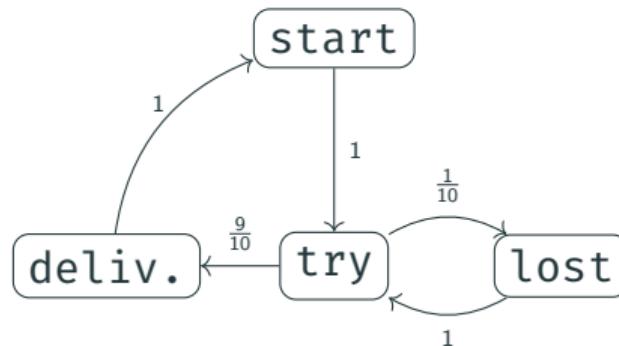


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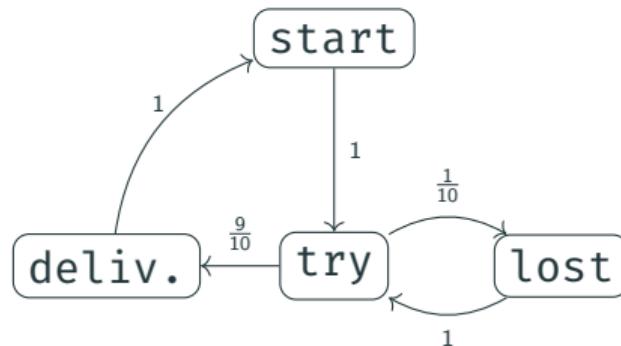


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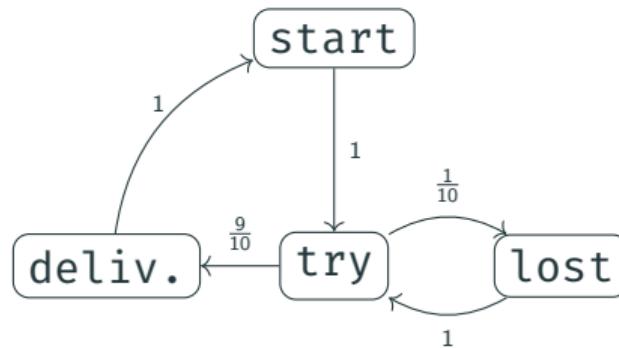


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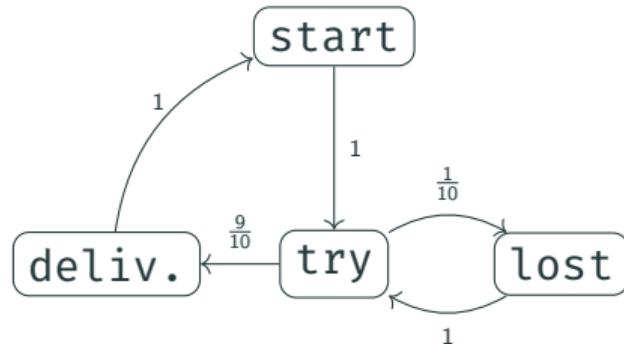
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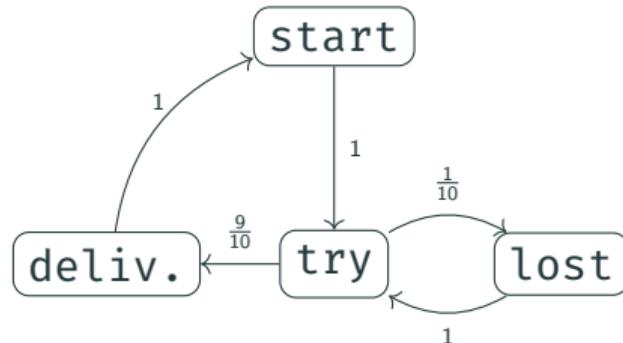
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Sure reachability



It seems obvious that starting from `start` (or indeed, any state), the desirable state `delivered` will almost surely be reached.

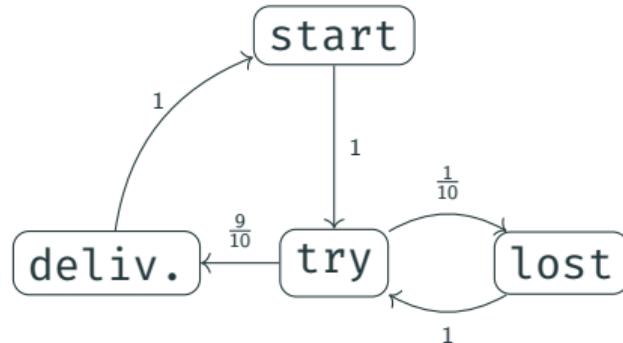
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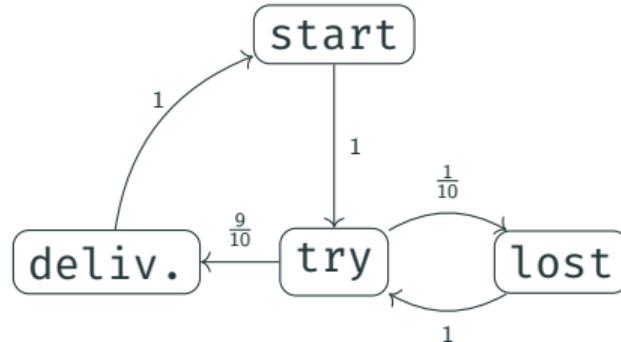
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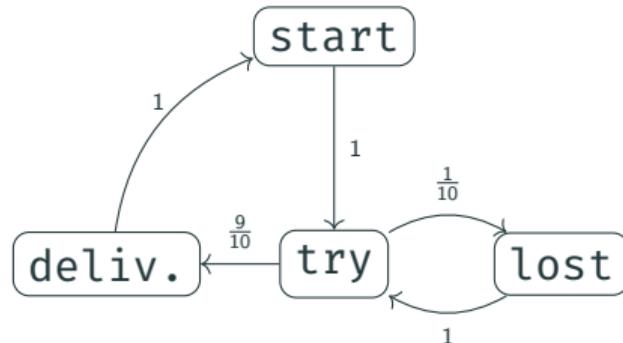
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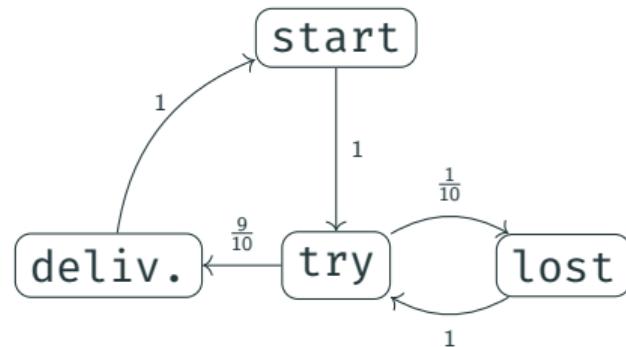
It seems obvious that starting from `start` (or indeed, any state), the desirable state `delivered` will almost surely be reached.

1. The probability to get from `start` to `delivered` is > 0 ;
2. we can't get stuck anywhere.

We can even say more: **every state is reachable from every other**.

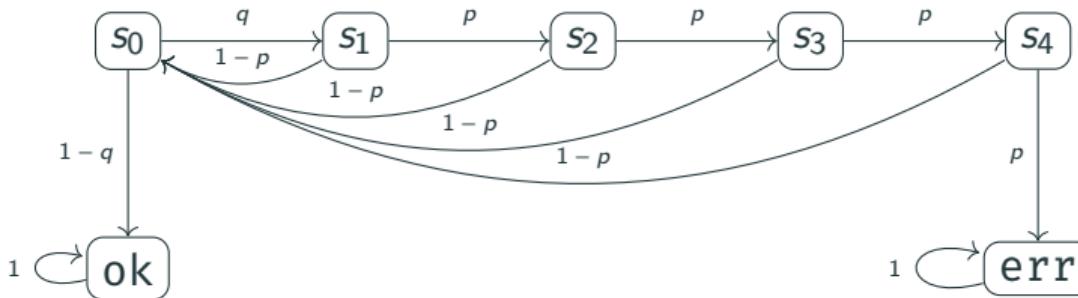
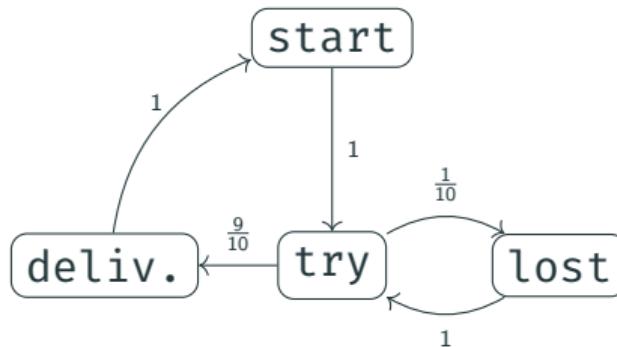
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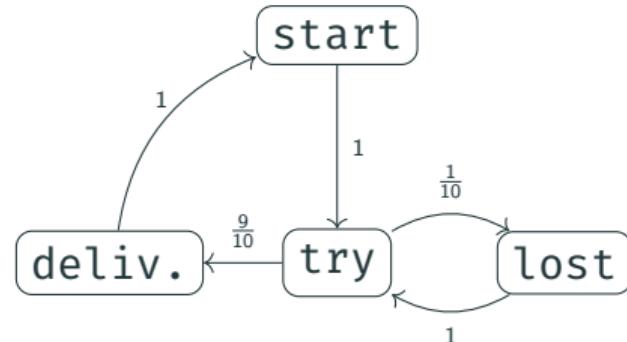


Theorem (sure reachability)

If (X, γ) is a strongly connected finite Markov chain and $x \in X$ is a state, then the probability of eventually reaching x (starting from anywhere) is 1:

$$X \models \mathbb{P}(\Diamond x) = 1.$$

Recurrence



But that's not all. Not only do we almost surely reach delivered, but we almost surely reach it **infinitely often**.

Theorem (finite reachability)

If (X, γ) is a strongly connected finite Markov chain and $x \in X$ is a state, then the probability of eventually reaching x (starting from anywhere) is 1:

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Theorem (finite recurrence)

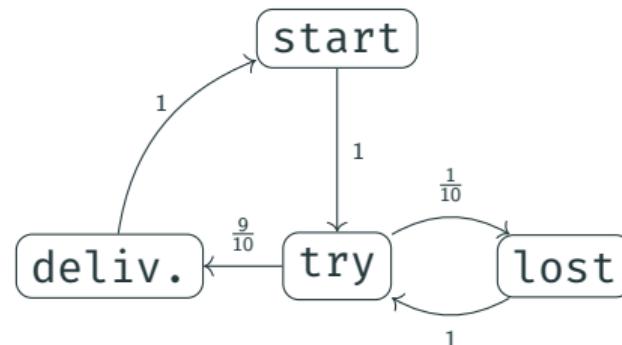
If (X, γ) is a strongly connected finite Markov chain and $x \in X$ is a state, then the probability of reaching x **infinitely often** (starting from anywhere) is 1:

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Recurrence

Key point

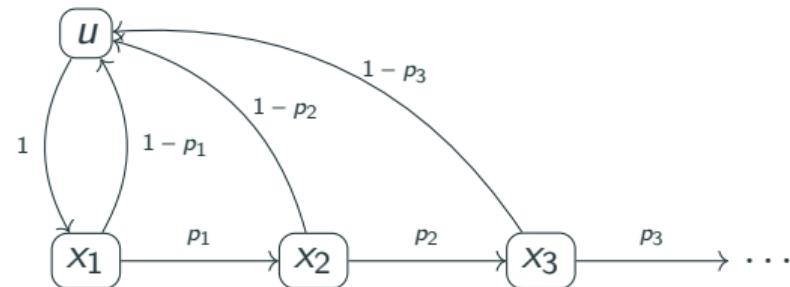
If a process evolves in a **finite and strongly connected** Markov chain, and A is a set of “good states”, then the process is guaranteed (in a probabilistic sense) to reach A infinitely often.



In our previous example, $A = \{\text{delivered}\}$.

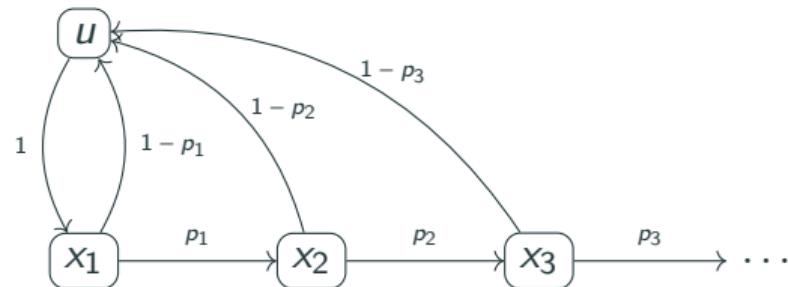
Recurrence

What if our probabilistic process has infinitely many states?



Recurrence

What if our probabilistic process has infinitely many states?



Today's objective

Generalize the recurrence theorem to infinite Markov chains.

今日の目標!

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(usually, X is a discrete measurable space, so that every singleton $\{x\}$ is a measurable event)

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The generalization seems obvious:

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Example

$X = \mathbb{R}$, $\gamma(x) = \mathcal{N}(x, 1)$.

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To state a recurrence theorem, we also need a notion of **reachability**:

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We say that a state $y \in X$ is **reachable** from $x \in X$ if either $x = y$,

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But wait a minute, in our previous example where $X = \mathbb{R}$ and $\gamma(x) = \mathcal{N}(x, 1)$, we have $\gamma(x, y) = 0$ for all $x, y \in X$. **No state is reachable from x !** (except x itself)

Infinite Markov chains (the right way)

Solution

Instead of focusing on whether or not $\gamma(x, y) > 0$, we should instead ask if $\gamma(x, U) > 0$ for any “arbitrary small set” $U \ni y$.

Of course we can't just take U to be a measurable set since in most cases $\{y\}$ is measurable...

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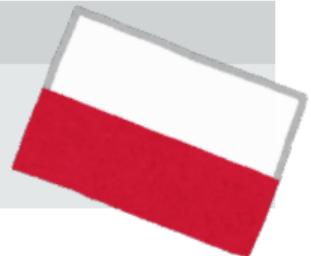
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Instead of focusing on whether or not $\gamma(x, y) > 0$, we should instead ask if $\gamma(x, U) > 0$ for any “arbitrary/small set” **open set** $U \ni y$.

Of course we can't just take U to be a measurable set since in most cases $\{y\}$ is measurable... So we turn to **topology**.

Nugget of wisdom 1

Topology + probability theory = Polish spaces



A Polish space is a topological space that is separable (it admits a dense countable subset) and completely metrizable (its topology is generated by a metric under which every Cauchy sequence converges).

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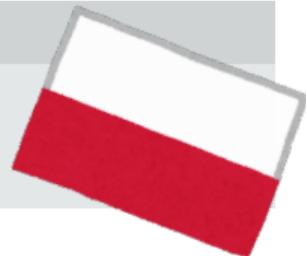
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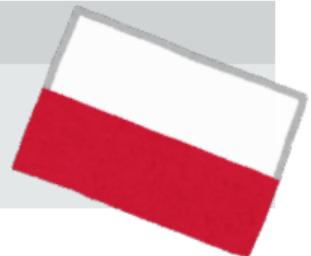
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In other words, a Markov chain is a **Δ -coalgebra**.

Here, Δ is the **Giry monad**, which maps X to the space of probability distributions over the Borel algebra $(X, B(X))$, with the so-called “weak topology”.

Objective

We want to generalize our finite recurrence theorem:

Theorem (finite recurrence)

If (X, γ) is a strongly connected finite Markov chain and $E \subseteq X$ a non-empty measurable set, then reaching E infinitely often (starting from anywhere) is almost certain, i.e.

$$X \models \mathbb{P}(\square \diamond E) = 1.$$

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Theorem??

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If (X, γ) is a strongly connected ~~finite~~ topological Markov chain and $U \subseteq X$ a non-empty **open** set, then reaching U infinitely often (starting from anywhere) is almost certain, i.e.

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1. What is the $\mathbb{P}(\square \diamond U)$ at a state $x \in X$? i.e. how to define the probability to follow a random walk that satisfies $\square \diamond U$?
2. What does “strongly connected” means?

Path spaces

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3. if $n = \infty$,

$$X^{\odot \infty} = \lim \left(\dots \longrightarrow X^{\odot n} \longrightarrow X^{\odot(n-1)} \longrightarrow \dots \longrightarrow X^{\odot 2} \longrightarrow X \right)$$

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2. $X^{\odot \infty} \subseteq X^\infty$ is the subspace of all sequences $(x_i)_{i \in \mathbb{N}}$ such that x_{i+1} is reachable in one step from x_i ;



Proposition

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Let's sketch the proof. Since $\mathcal{P}ol$ has countable limits, it is enough to show that $X^{\odot 2}$ is a Polish space.

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Recall that $X^{\odot 2} \subseteq X^2$ is the subspace of all pairs (x, y) such that $y \in \text{supp } \gamma(x)$.

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Problem

$g_U : X^2 \rightarrow \mathbb{R}$ is not continuous in general.

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The solution is to replace

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Using some topological arguments, we get

$$X^{\odot 2} = \bigcap_{q,n} \tilde{g}_{q,n}^{-1}(0, +\infty).$$

Proposition

The Borel algebra of $X^{\odot n}$ is generated by sets of the form

$$E_1 \odot \cdots \odot E_n := X^{\odot n} \cap (E_1 \times \cdots \times E_n)$$

called **sequence sets**, where $E_1, \dots, E_n \in B(X)$.

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Extension of probability measures

Motivation

Thanks to $X^{\odot n}$, we have a good notion of reachability and paths, a.k.a. random walks.

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But what is the probability to follow a random walk within a subset $E \subseteq X^{\odot \infty}$?

Objective

We need to lift an initial distribution μ on X to a distribution $\text{ext}_\infty \mu$ on $X^{\odot \infty}$.

Extension of probabilities

Given a probability distribution μ on X (that acts as an initial distribution), we define a distribution $\text{ext}_\infty \mu$ on $X^{\odot\infty}$ as follows: the probability

$$\text{ext}_\infty \mu(\text{Cyl}(E_1, \dots, E_n))$$

to walk from E_1 to E_2 to ... to E_n , is

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But we are not interested in any V , we would like

$$\diamond U, \quad \square \diamond U$$

where $U \subseteq X$ is open.

Logic

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We develop two logics:

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LTL is defined as

$$\phi ::= \top \mid \neg\phi \mid \phi \wedge \phi \mid E \mid \circ\phi \mid \phi \mathbf{U}^{\leq n} \phi$$

where $E \in B(X)$ and $n \leq \infty$.

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The semantic of LTL

The two modalities we're really interested in are

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Observation

The LTL formula we're really interested in is $\square \diamond U$:

$$[\![\square \diamond U]\!] = \{(x_i)_{i \in \mathbb{N}} \in X^{\odot\infty} \mid x_i \in U \text{ for infinitely many } i \in \mathbb{N}\}.$$

Recurrence theorem



Theorem??

If (X, γ) is a strongly connected ~~finite~~ **topological** Markov chain and $U \subseteq X$ a non-empty **open** set, then reaching U infinitely often (starting from anywhere) is almost certain, i.e.

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$\square \lozenge U$ = “it is always true that eventually, we’ll reach U ”

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2. (atomic predicates) $[E] := E$;
3. $\mathbb{P}(\phi) \geq p$ means that “the probability to start walking in a way that satisfies ϕ is $\geq p$ ”

$$[\mathbb{P}(\phi) \geq p] := \{x \in X \mid \text{ext}_\infty \delta_x ([\phi]) \geq p\}$$

The semantic of PCTL

Quick dissection:



$$[\![\mathbb{P}(\phi) \geq p]\!] := \{x \in X \mid \text{ext}_\infty \delta_x([\![\phi]\!]) \geq p\}$$

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If (X, γ) is a strongly connected ~~finite~~ **topological** Markov chain and $U \subseteq X$ a non-empty **open** set, then reaching U infinitely often (starting from anywhere) is almost certain, i.e.

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i.e. $X = [\mathbb{P}(\square \diamond U) = 1]$

The recurrence theorem(s)

Recurrence theorem: first attempt

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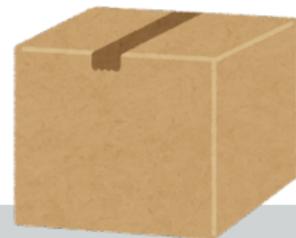
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So it seems finiteness, or smallness, is important to prevent random walks from straying forever.



Nugget of wisdom 2

Topology + “smallness” = compactness

We say that a Markov chain (X, γ) is **compact** if X is a compact topological space.

Recurrence theorem: second attempt

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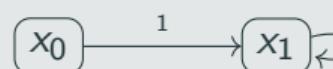


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Recurrence theorem: weak version



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Recall that “strong connectedness” means (in the finite discrete case): every state is reachable from every other.

Strong connectedness?



Key observation

If (X, γ) is a (finite and discrete) strongly connected Markov chain, i.e. if every state is reachable from every other, then surely there cannot exist a proper **subchain** $(Y, \gamma|_Y) \subseteq (X, \gamma)$. Random walks in Y could possibly “escape” outside of Y .

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Definition

A topological Markov chain is *irreducible* if it does not have any proper subchains.

Example



Example



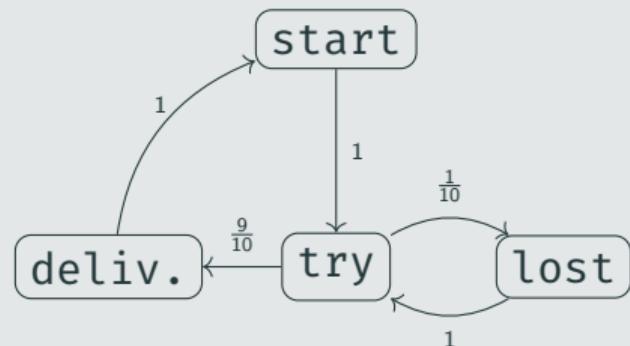
Example



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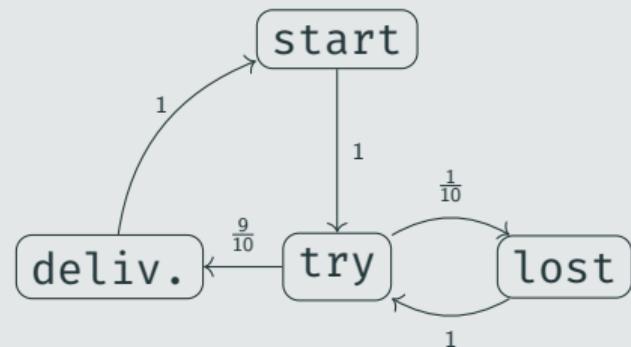
Irreducible Markov chains

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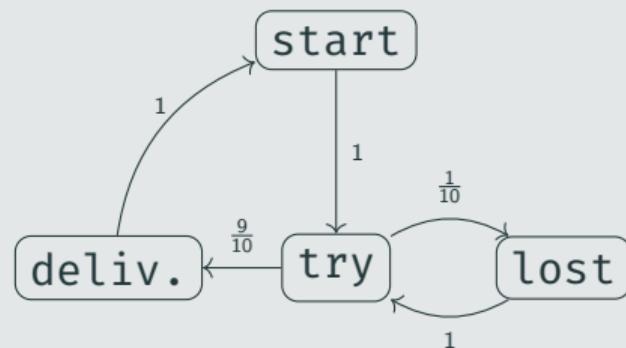
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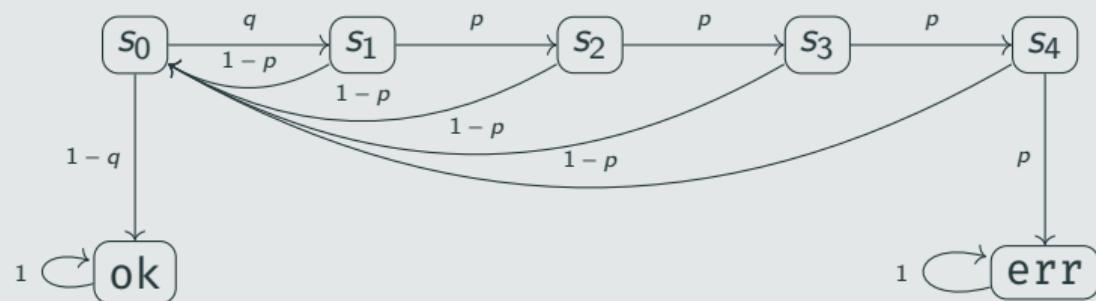
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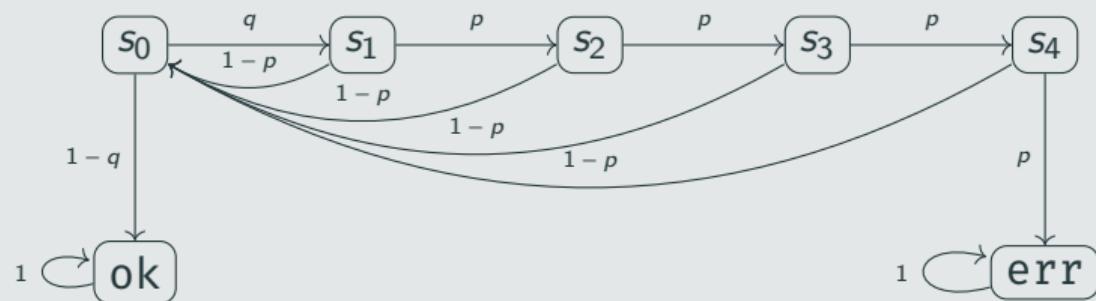
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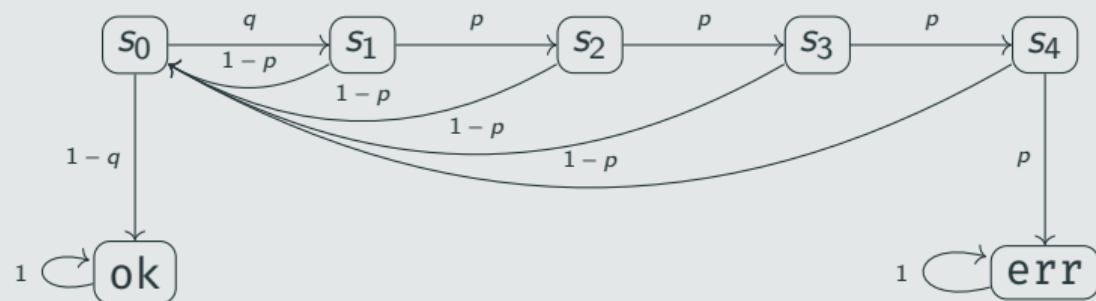
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Recurrence theorem: strong version

This intuition leads to our second recurrence theorem



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Theorem (strong recurrence, but better) ✓

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If (X, γ) is a strongly connected finite Markov chain and $x \in X$ is a state, then x is almost certainly reached infinitely often from everywhere, i.e. $X \models \mathbb{P}(\Box \Diamond x) = 1$.

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Next steps

Question 1

Does every Markov chain necessarily admit an irreducible subchain?

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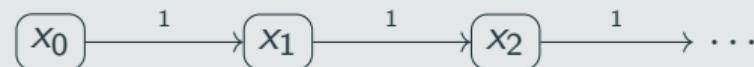
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What about **compact** chains?

Question 2

If so, does every random walk necessarily end in an irreducible subchain?

$$X \models \mathbb{P} \left(\Diamond \bigcup_{Y \text{ irred.}} Y \right) = ?$$

Next steps

Similar recurrence results are known in the field of dynamical systems.

Poincaré's recurrence theorem

Let X be a measurable space, $\mu \in \Delta X$, $f: X \rightarrow X$ be measure preserving (i.e. $\mu = \mu f^{-1}$), and $U \subseteq X$ be such that $\mu(U) > 0$. For almost all $x \in U$, $\mathbb{P}(\square \diamond U) = 1$.

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Investigate connections between dynamical systems and Markov chains? How does our recurrence theorems transfer? How does the logical side transfer?

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3. “Higher Markov chains” using simplicial sets. Geometrical detection of recurrence phenomena?

Now for some gory details

Where is the difficulty coming from?

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Where is the difficulty coming from? The subtle structure of the **Giry monad**
 $\Delta : \mathcal{P}ol \longrightarrow \mathcal{P}ol$.

The Giry monad

There are two Giry monads

$$\Delta : \mathcal{M}\text{eas} \longrightarrow \mathcal{M}\text{eas}, \quad \Delta : \mathcal{P}\text{ol} \longrightarrow \mathcal{P}\text{ol}$$

The Giry monad on $\mathcal{M}\text{eas}$

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The unit $\delta : X \rightarrow \Delta X$ maps x to its Dirac distribution δ_x .

Lemma

Equivalently, Σ_Δ is the coarsest σ -algebra such that for all measurable and bounded map $f: X \rightarrow \mathbb{R}$, the map

$$\begin{aligned} I_f: \Delta X &\longrightarrow \mathbb{R} \\ \mu &\longmapsto \int f \, d\mu \end{aligned}$$

is measurable. In other words, Σ_Δ is the *coarsest σ -algebra w.r.t. integration of measurable maps*.

The Giry monad on $\mathcal{P}ol$, the wrong way

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We also need $\delta: X \rightarrow \Delta X$ to be continuous if we want a monad $\Delta: \mathcal{P}ol \rightarrow \mathcal{P}ol$.

The Giry monad on $\mathcal{P}ol$, the wrong way

But here's the problem, for any measurable $f: X \rightarrow \mathbb{R}$, the following triangle commutes:

$$\begin{array}{ccc} X & \xrightarrow{f} & \mathbb{R} \\ & \searrow \delta & \swarrow l_f \\ & (\Delta X, \mathcal{T}_{\text{wrong}}) & \end{array}$$

so X has the property that every measurable map is continuous, which forces X to be discrete...

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Correct definition

ΔX is the set of probability measures on $(X, \mathcal{B}(X))$ with the coarsest topology \mathcal{T}_Δ such that for all ~~measurable~~ **continuous** and bounded map $f: X \rightarrow \mathbb{R}$, the map

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The Giry monad on $\mathcal{P}ol$

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Why is this definition such a problem? $\mathcal{T}_{\text{wrong}}$ is simple, but the only control we have over \mathcal{T}_Δ is

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Proving that a map $\Delta X \rightarrow Y$ is continuous is hard!

Extension of probability measures

For example, we were unable to prove that

$$\text{ext}_n : \Delta X \longrightarrow \Delta X^{\odot n}$$

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is continuous, where $2 \leq n \leq \infty$. Still,

Proposition

$\text{ext}_n : \Delta X \longrightarrow \Delta X^{\odot n}$ is **measurable**, for $n \leq \infty$.

Extension of probability measures

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Fact

The Borel algebra of $\Delta(X^{\odot n})$ is generated by

$$\beta^{\bowtie p}(E_1 \odot \cdots \odot E_n) := \left\{ \nu \in \Delta(X^{\odot n}) \mid \nu(E_1 \odot \cdots \odot E_n) \bowtie p \right\}$$

where $\bowtie \in \{<, \leq, \geq, >\}$, $p \in [0, 1]$, and $E_1, \dots, E_n \in \mathcal{B}(X)$.

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Corollary

It is enough to show that

$$\text{ext}_n^{-1}(\beta^{\bowtie p}(E_1 \odot \cdots \odot E_n))$$

is measurable in ΔX .

Extension of probability measures

Recall that for $\mu \in \Delta X$,

$$\text{ext}_n \mu(E_1 \odot \cdots \odot E_n) = \int_{x_1 \in E_1} \int_{x_2 \in E_2} \cdots \int_{x_{n-1} \in E_{n-1}} \mu(dx_1) \times \gamma(x_1, dx_2) \times \cdots \times \gamma(x_{n-1}, E_n).$$

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by induction, f is bounded measurable! So integrating w.r.t. to f is a measurable operation, i.e. $\text{ext}_n \mu(E_1 \odot \cdots \odot E_n)$ is measurable in μ .

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by induction, f is bounded measurable! So integrating w.r.t. to f is a measurable operation, i.e. $\text{ext}_n \mu(E_1 \odot \cdots \odot E_n)$ is measurable in μ . Since $\text{ext}_n(-)(E_1 \odot \cdots \odot E_n)$ is measurable for all $E_1, \dots, E_n \in B(X)$, we conclude that $\text{ext}_n(-)$ is measurable.

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which is measurable in μ . Since $\text{ext}_\infty(-)(\text{Cyl}(E_1, \dots, E_k))$ is measurable for every cylinder set $\text{Cyl}(E_1, \dots, E_k)$, we conclude that $\text{ext}_\infty(-)$ is measurable.

Extension of probability measures

To summarize, for $n \leq \infty$

$$\text{ext}_n : \Delta X \longrightarrow \Delta X^{\odot n}$$

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To summarize, for $n \leq \infty$

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is measurable.

BUT we do not know if it is continuous and we will have to work around that...

The weak recurrence theorem

We want to prove

Theorem (weak recurrence)

Let (X, γ) be a compact topological Markov chain and $U \subseteq X$ an open set. If $X \models \mathbb{P}(\Diamond U) > 0$, then

$$X \models \mathbb{P}(\Box \Diamond U) = 1.$$

for the sake of exposition, we will work backwards.

The weak recurrence theorem

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Theorem (weak ~~recurrence~~ reachability)

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If U is reached from everywhere with probability 1, then surely it is reached infinitely often.

The weak recurrence theorem

Theorem (“reachability soon”)

Let (X, γ) be a compact topological Markov chain and $U \subseteq X$ an open set. If $X = [\![\mathbb{P}(\Diamond U) > 0]\!]$, then

$$X = [\![\mathbb{P}(\Diamond^{\leq k} U) > r]\!]$$

for some k and r .

If U is reached soon ($\leq k$) with probability $> r$, then surely, avoiding U forever is impossible, i.e.

$$X = [\![\mathbb{P}(\Diamond^{\leq k} U) > r]\!] \iff X = [\![\mathbb{P}(\Diamond U) = 1]\!].$$

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So we need to show that there exist $k \in \mathbb{N}$ and $r \in [0, 1]$ such that

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BUT we need to know that the $R_{k,n}$'s are **closed**!

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In other words,

$$R_{k,n} = \Upsilon_k^{-1}[1 - 1/n, 1]$$

where $\Upsilon_k : x \mapsto \text{ext}_{k+1} \delta_x(\bar{U} \odot \dots \odot \bar{U})$.

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So we have $\Upsilon_k : x \longmapsto \text{ext}_{k+1} \delta_x (\bar{U} \odot \cdots \odot \bar{U})$,

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But there is a way out: it is enough to show that Υ_k is **upper semicontinuous (USC)**.

Definitions

A map $f : X \rightarrow \mathbb{R}$ is USC if for all $r \in \mathbb{R}$, $f^{-1}[r, +\infty)$ is closed.

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The case $k \geq 2$ can be deduced from induction, so let's focus on $k = 1$.

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Therefore, $x \in A_r$, and A_r is closed. This concludes the proof that $\gamma(-, \bar{U})$ is USC.

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- ... so $X = [\![\mathbb{P}(\Diamond U) = 1]\!]$, i.e. " U certainly happens eventually", this is the **weak reachability theorem**

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- ... so $\Upsilon_k : x \mapsto \text{ext}_{k+1} \delta_x(\bar{U} \odot \dots \odot \bar{U})$ is USC
- ... so $R_{k,n} = [\![\mathbb{P}(\Diamond^{\leq k} U) \leq 1/n]\!] = \Upsilon_k^{-1}[1 - 1/n, 1]$ is closed
- ... so there exist $k, n \in \mathbb{N}$ such that $R_{k,n} = [\![\mathbb{P}(\Diamond^{\leq k} U) \leq 1/n]\!] = \emptyset$, since $\bigcap_{k,n} R_{k,n} = \emptyset$ and X is compact
- ... so $X = [\![\mathbb{P}(\Diamond^{\leq k} U) > 1/n]\!]$, i.e. " U probably happens soon"
- ... so $X = [\![\mathbb{P}(\Diamond U) = 1]\!]$, i.e. " U certainly happens eventually", this is the **weak reachability theorem**
- ... so $X = [\![\mathbb{P}(\Box \Diamond U) = 1]\!]$, i.e. " U happens infinitely often", this is the **weak recurrence theorem**



From weak to strong

Theorem (weak recurrence)

Let (X, γ) be a compact topological Markov chain and $U \subseteq X$ an open set. If $X \models \mathbb{P}(\Diamond U) > 0$, then

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Using weak recurrence, it is enough to show that $X \models \mathbb{P}(\Diamond U) > 0$. But this proof is not very interesting or insightful so let's move on

Topological & pathological

Polish spaces are fairly well-behaved. But topological Markov chains are not. Let's go over some frustrating counterexamples.



The weak recurrence theorem

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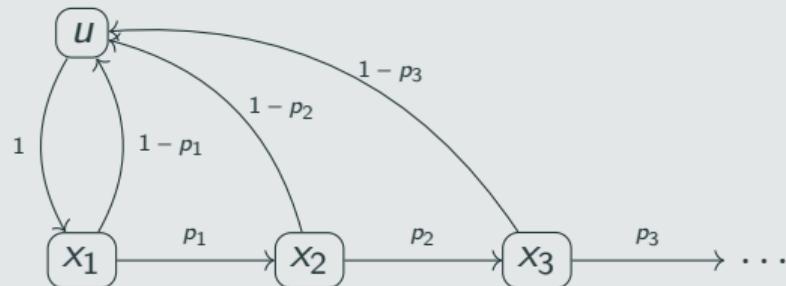
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Counterexample

Consider the discrete chain

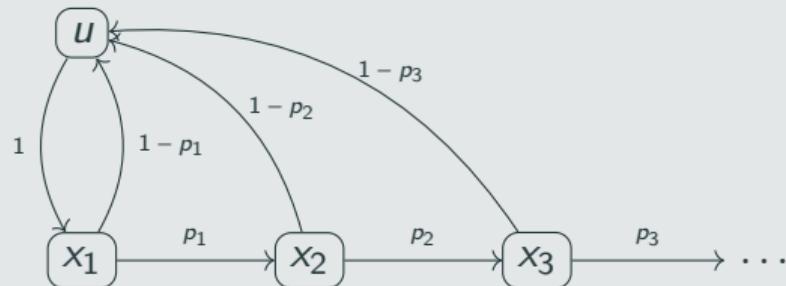


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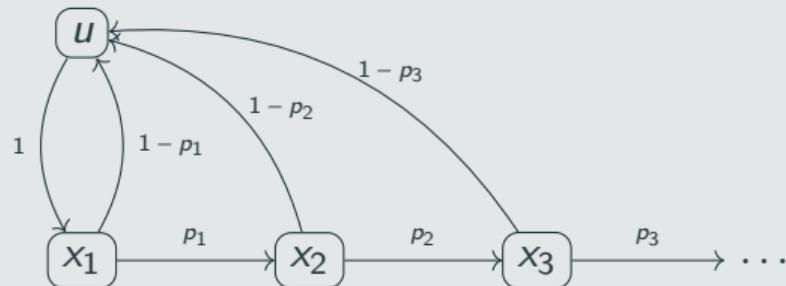


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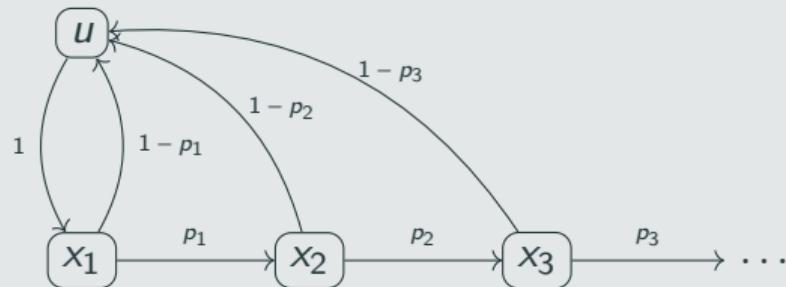


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where $p_i := 1 - \frac{1}{(i+1)^2}$. u is reachable from everywhere, i.e. $X \models \mathbb{P}(\Diamond\{u\}) > 0$.
Unfortunately,

$$\delta_{x_1}(\Diamond\{u\}) = 1 - \text{ext}_\infty \delta_{x_1}(\{(x_1, x_2, \dots)\}) = 1 - \prod_{i=1}^{\infty} \left(1 - \frac{1}{(i+1)^2}\right) = \frac{1}{2}.$$

Even with reachability, the compactness criterion is necessary!

Subchains

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Simply consider $X = \mathbb{R}$ and $\gamma(x) = \delta_x$, i.e. every state can only transition to itself. Every subset is a subchain.

However

Lemma

If $Y \subseteq X$ is irreducible, then it is measurable.

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Therefore,

$$Y = \bigcup_{y \in Y} \text{supp } \gamma(y) = \bigcup_{q \in Q} \text{supp } \gamma(q)$$

is a countable union of closed sets.

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Take $X := \{x_0, x_1\}$ with the discrete topology, and $\gamma(x_i) := \delta_{x_{1-i}}$. Then X itself is irreducible but not connected.

Reachability property

Definition

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The reachability property is an important notion to establish the strong recurrence theorem.

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This Markov chain clearly has the reachability property, but it is not irreducible, for $Y := (0, 1]_A + (0, 1]_B$ is a proper subchain.

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2. We saw how to walk around problems in the proof of the weak recurrence theorem.
3. We saw some basic counterexamples.