

Imprecise-probabilistic processes – Part I

Alexander Erreygers

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Uncertain process

We consider a system whose uncertain state X_t
takes values in the state space \mathcal{X} and
changes over time $t \in \mathbb{T}$.



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Uncertain process

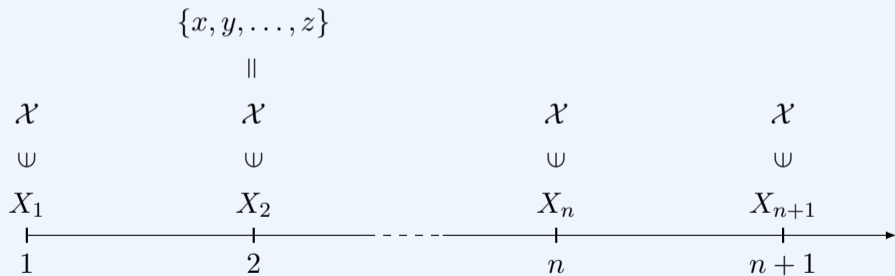
We consider a system whose **uncertain state** X_t
takes values in the **state space** \mathcal{X} and
changes over **time** $t \in \mathbb{T}$.

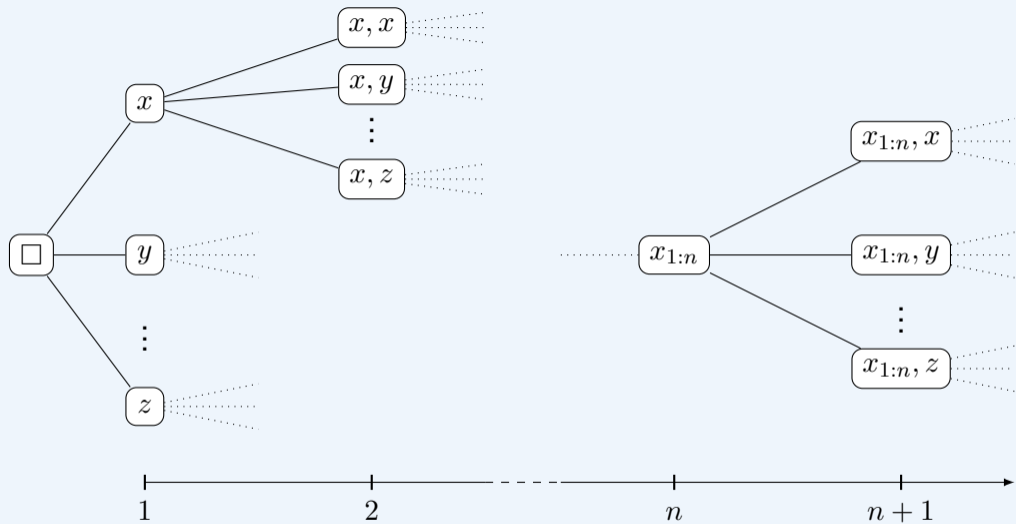
Uncertain process

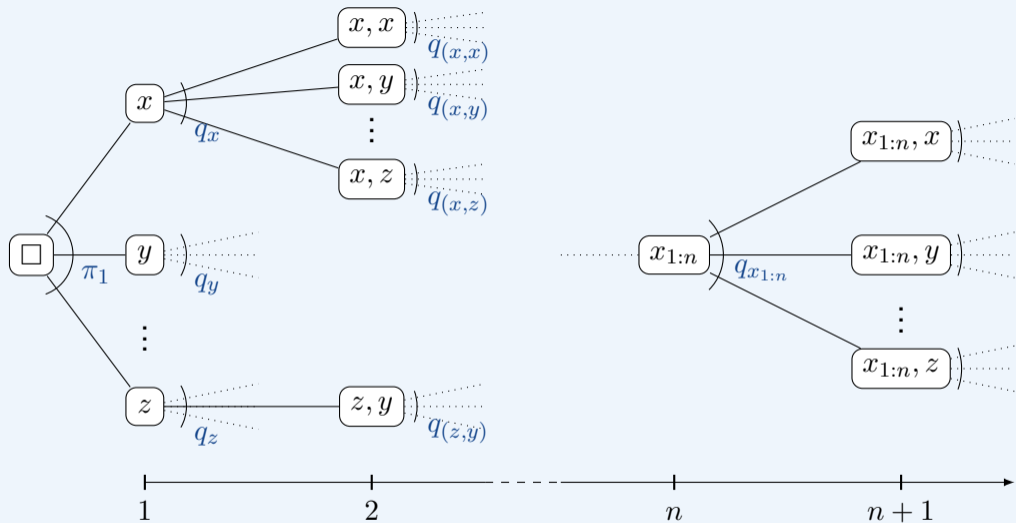
We consider a system whose uncertain state X_t
takes values in the state space \mathcal{X} and
changes over time $t \in \mathbb{T}$.

For now, let us focus on **finite-state** and **discrete-time** uncertain processes, so with
 \mathcal{X} finite and $\mathbb{T} = \mathbb{N} = \{1, 2, 3, \dots\}$.









Precise probability tree

$$\pi_1 \in \Sigma_{\mathcal{X}}$$

$$(\forall n \in \mathbb{N}, x_{1:n} \in \mathcal{X}^n) q_{x_{1:n}} \in \Sigma_{\mathcal{X}}$$

$$P(X_1 = x) = \pi_1(x)$$

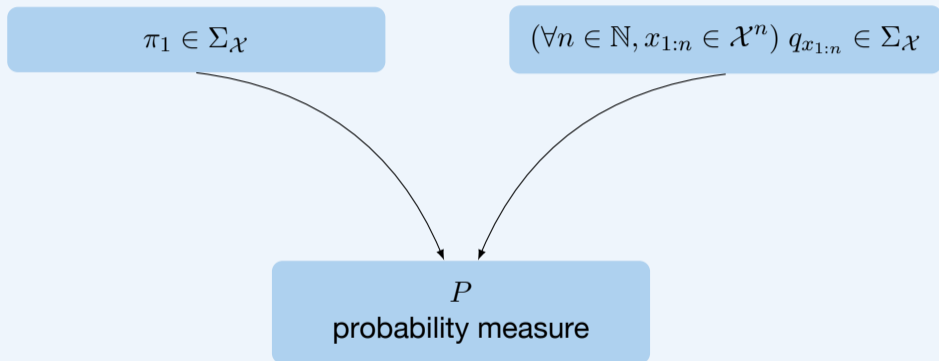
Precise probability tree

$$\pi_1 \in \Sigma_{\mathcal{X}}$$

$$(\forall n \in \mathbb{N}, x_{1:n} \in \mathcal{X}^n) q_{x_{1:n}} \in \Sigma_{\mathcal{X}}$$

$$P(X_{n+1} = x \mid X_1 = x_1, \dots, X_n = x_n) = q_{x_{1:n}}(x)$$

Precise probability tree



From local to global probabilities

For any $n > 1$ and $x_{1:n} = (x_1, \dots, x_n) \in \mathcal{X}^n$,

$$P(X_{1:n} = x_{1:n}) = P(X_1 = x_1, \dots, X_n = x_n).$$

From local to global probabilities

For any $n > 1$ and $x_{1:n} = (x_1, \dots, x_n) \in \mathcal{X}^n$,

$$\begin{aligned} P(X_{1:n} = x_{1:n}) &= P(X_1 = x_1, \dots, X_n = x_n) \\ &= P(X_{1:n-1} = x_{1:n-1})P(X_n = x_n \mid X_{1:n-1} = x_{1:n-1}). \end{aligned}$$

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From local to global probabilities

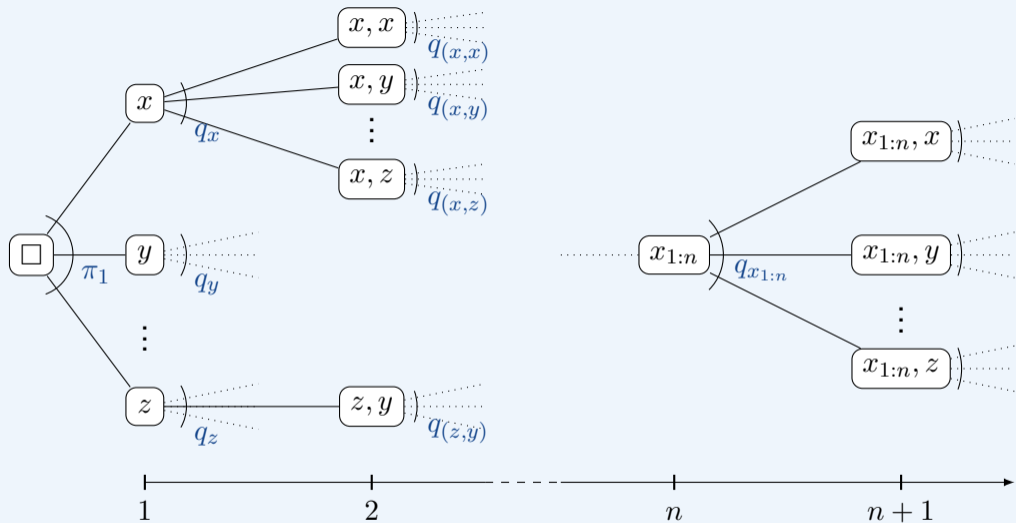
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From local to global probabilities

For any $n > 1$ and $x_{1:n} = (x_1, \dots, x_n) \in \mathcal{X}^n$,

$$\begin{aligned}P(X_{1:n} = x_{1:n}) &= P(X_1 = x_1, \dots, X_n = x_n) \\&= P(X_{1:n-1} = x_{1:n-1})P(X_n = x_n \mid X_{1:n-1} = x_{1:n-1}) \\&= P(X_{1:n-1} = x_{1:n-1})q_{x_{1:n-1}}(x_n) \\&= \dots \\&= P(X_1 = x_1)P(X_2 = x_2 \mid X_1 = x_1)q_{x_{1:2}}(x_3) \cdots q_{x_{1:n-1}}(x_n) \\&= \pi_1(x_1)q_{x_1}(x_2) \cdots q_{x_{1:n-1}}(x_n).\end{aligned}$$

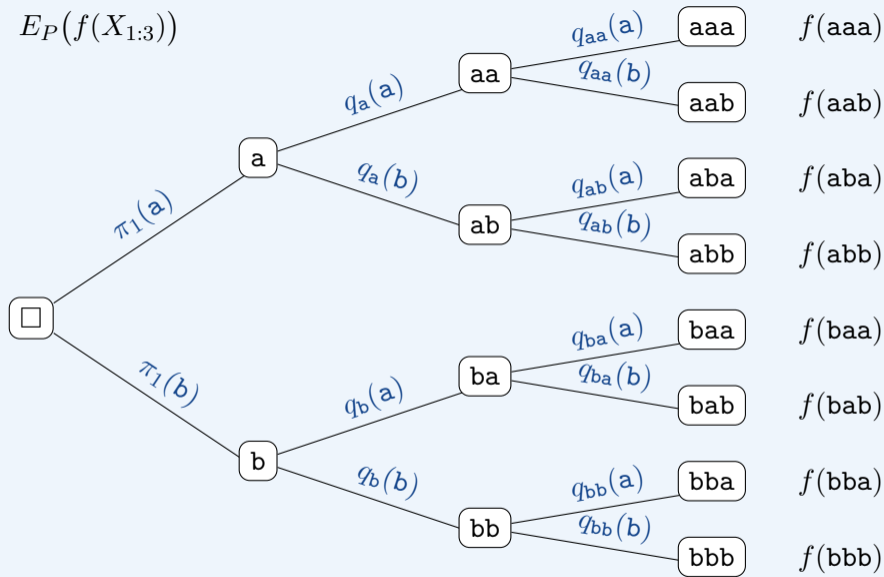


From local probabilities to global expectations

For $n \in \mathbb{N}$ and $f: \mathcal{X}^n \rightarrow \mathbb{R}$,

$$\begin{aligned} E(f(X_{1:n})) &= \sum_{x_{1:n} \in \mathcal{X}^n} f(x_{1:n}) P(X_{1:n} = x_{1:n}) \\ &= \sum_{x_{1:n} \in \mathcal{X}^n} f(x_{1:n}) \pi_1(x_1) q_{x_1}(x_2) \cdots q_{x_{1:n-1}}(x_n). \end{aligned}$$

$E_P(f(X_{1:3}))$



From local probabilities to global expectations

For $n \in \mathbb{N}$ and $f: \mathcal{X}^n \rightarrow \mathbb{R}$,

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From local probabilities to global expectations

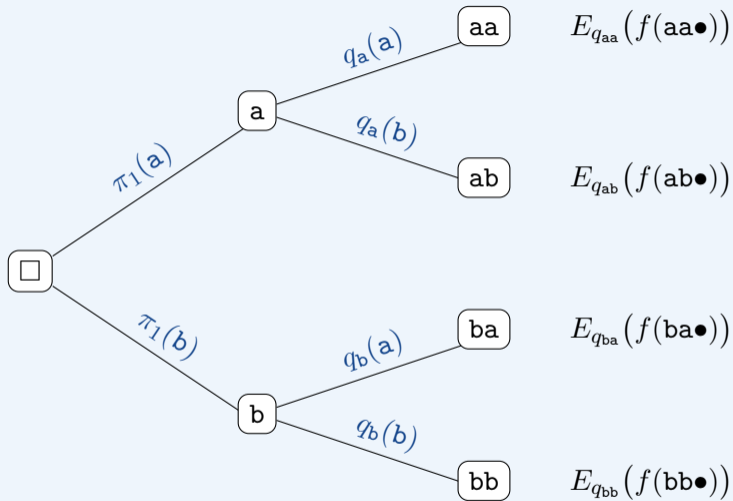
For $n \in \mathbb{N}$ and $f: \mathcal{X}^n \rightarrow \mathbb{R}$,

$$\begin{aligned} E(f(X_{1:n})) &= \sum_{x_{1:n} \in \mathcal{X}^n} f(x_{1:n}) P(X_{1:n} = x_{1:n}). \\ &= \sum_{x_{1:n} \in \mathcal{X}^n} f(x_{1:n}) \pi_1(x_1) q_{x_1}(x_2) \cdots q_{x_{1:n-1}}(x_n). \\ &= \sum_{x_1 \in \mathcal{X}} \pi_1(x_1) \sum_{x_2 \in \mathcal{X}} q_{x_1}(x_2) \cdots \sum_{x_n \in \mathcal{X}} q_{x_{1:n-1}}(x_n) f(x_{1:n}) \\ &= E(g(X_{1:n-1})) \end{aligned}$$

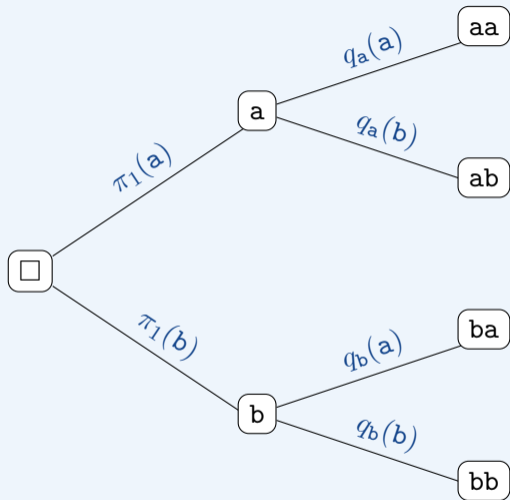
with

$$g: \mathcal{X}^{n-1} \rightarrow \mathbb{R}: x_{1:n-1} \mapsto E_{q_{x_{1:n-1}}} \left(\underbrace{f(x_{1:n-1} \bullet)}_{\mathcal{X} \rightarrow \mathbb{R}: x_n \mapsto f(x_{1:n})} \right).$$

$$E_P(f(X_{1:3}))$$



$$E_P(f(X_{1:3})) = E_P(g(X_{1:2}))$$



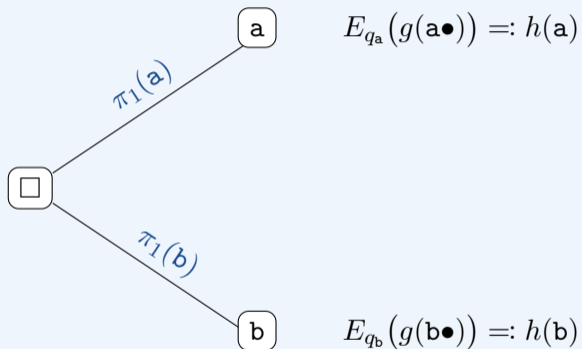
$$E_{q_{aa}}(f(aa\bullet)) =: g(aa)$$

$$E_{q_{ab}}(f(ab\bullet)) =: g(ab)$$

$$E_{q_{ba}}(f(ba\bullet)) =: g(ba)$$

$$E_{q_{bb}}(f(bb\bullet)) =: g(bb)$$

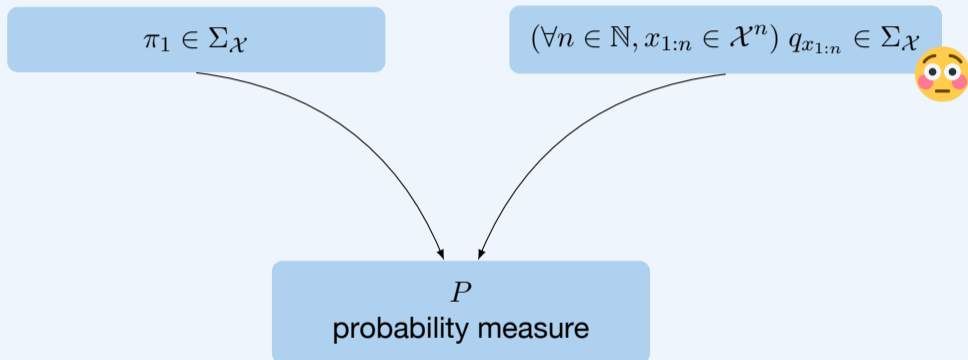
$$E_P(f(X_{1:3})) = E_P(h(X_1))$$





$$E_{\pi_1}(h) = E_P(f(X_{1:3}))$$

Precise probability tree



The Markov assumption

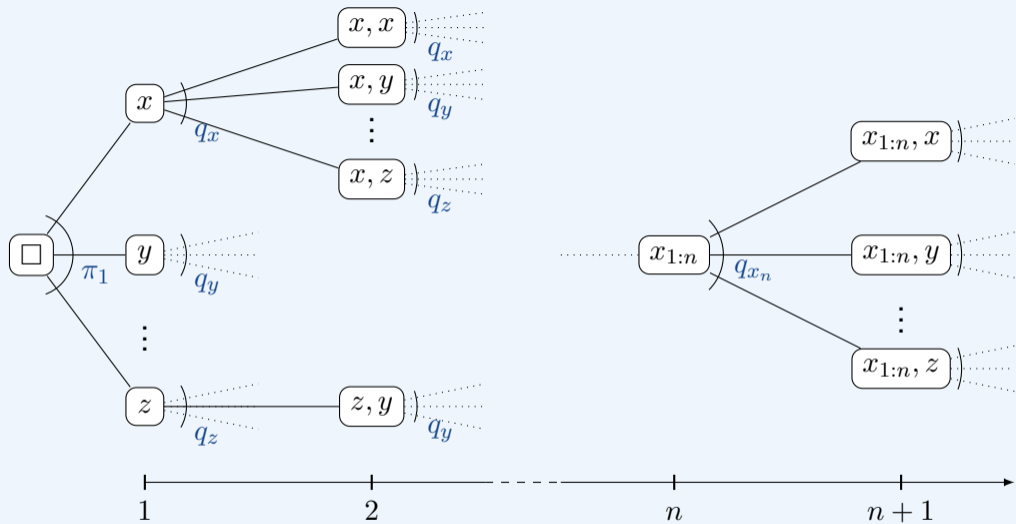
For all $n > 1$, $x_{1:n} = (x_1, \dots, x_n) \in \mathcal{X}^n$ and $y \in \mathcal{X}$, we're going to assume that

$$\begin{aligned} P(X_{n+1} = y \mid X_1 = x_1, \dots, X_{n-1} = x_{n-1}, X_n = x_n) \\ = P(X_{n+1} = y \mid X_n = x_n) \end{aligned}$$

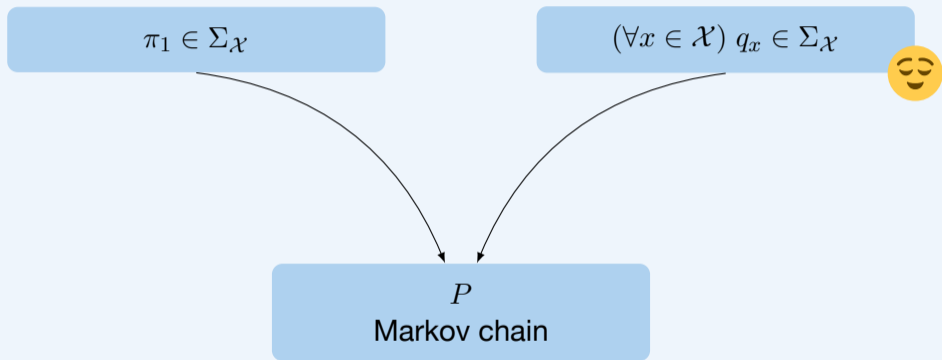
The Markov and time-homogeneity assumptions

For all $n > 1$, $x_{1:n} = (x_1, \dots, x_n) \in \mathcal{X}^n$ and $y \in \mathcal{X}$, we're going to assume that

$$\begin{aligned} P(X_{n+1} = y \mid X_1 = x_1, \dots, X_{n-1} = x_{n-1}, X_n = x_n) \\ &= P(X_{n+1} = y \mid X_n = x_n) \\ &= P(X_2 = y \mid X_1 = x_n). \end{aligned}$$



Markov chain



Markov chain

$$\pi_1 \in \Sigma_{\mathcal{X}}$$

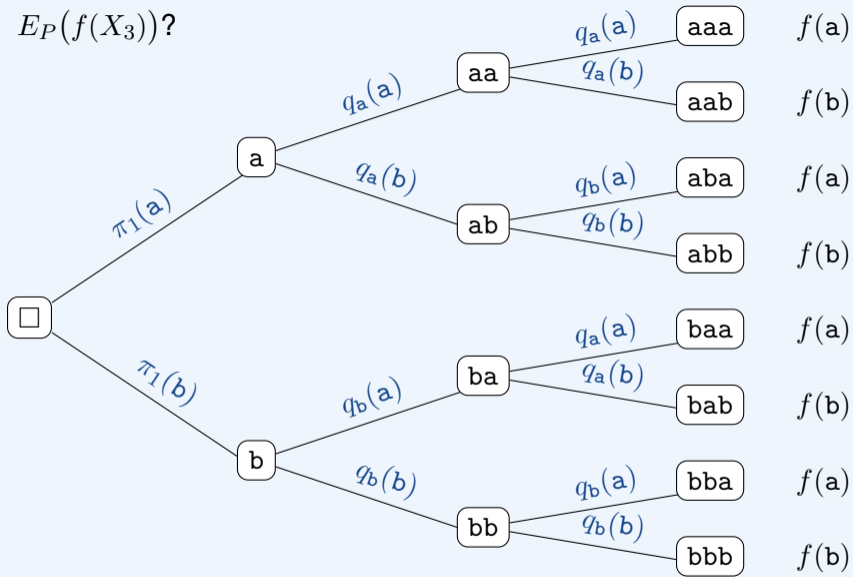
$$(\forall x \in \mathcal{X}) q_x \in \Sigma_{\mathcal{X}}$$

$$P(X_{n+1} = y \mid X_{1:n} = x_{1:n}) = P(X_{n+1} = y \mid X_n = x_n) = P(X_2 = y \mid X_1 = x_1)$$

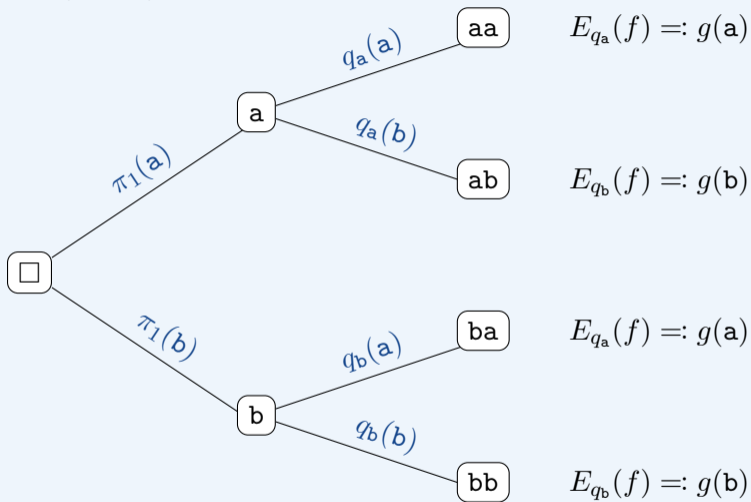
P
Markov chain



$E_P(f(X_3))?$



$$E_P(f(X_3)) = E(g(X_2))$$

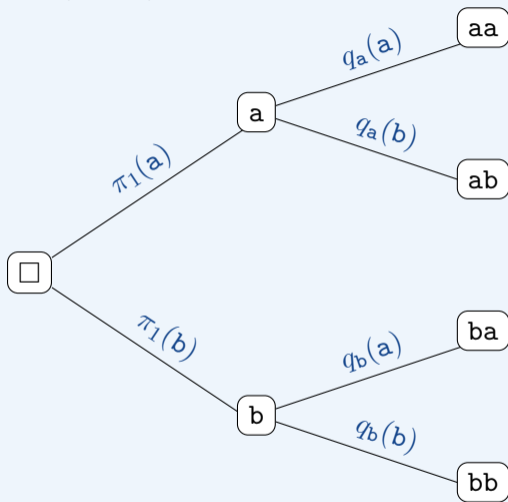


The transition operator

Let $T: \mathbb{R}^{\mathcal{X}} \rightarrow \mathbb{R}^{\mathcal{X}}$ be the corresponding *transition operator* which maps $f: \mathcal{X} \rightarrow \mathbb{R}$ to

$$Tf: \mathcal{X} \rightarrow \mathbb{R}: x \mapsto E_{q_x}(f) = \sum_{y \in \mathcal{X}} q_x(y) f(y).$$

$$E_P(f(X_3)) = E(\mathbb{T}f(X_2))$$



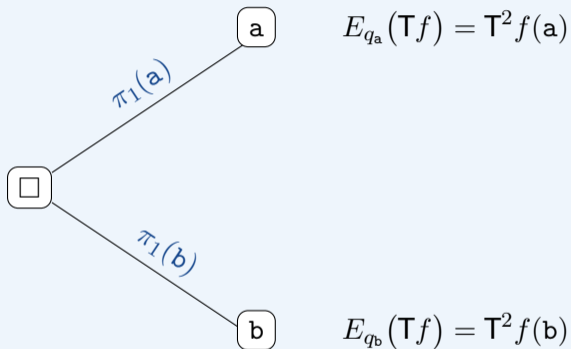
$$E_{q_a}(f) = \mathbb{T}f(a)$$

$$E_{q_b}(f) = \mathbb{T}f(b)$$

$$E_{q_a}(f) = \mathbb{T}f(a)$$

$$E_{q_b}(f) = \mathbb{T}f(b)$$

$$E_P(f(X_3)) = E(\mathbb{T}^2 f(X_1))$$



$$\square \quad E_{\pi_1}(\mathbb{T}^2 f) = E_P(f(X_3))$$

Global expectations via the transition operator

We've essentially shown that for all $n > 1$ and $f: \mathcal{X} \rightarrow \mathbb{R}$,

$$E(f(X_n)) = E_{\pi_1}(\mathsf{T}^{n-1}f).$$

Global expectations via the transition operator

We've essentially shown that for all $n > 1$ and $f: \mathcal{X} \rightarrow \mathbb{R}$,

$$E(f(X_n)) = E_{\pi_1}(\mathsf{T}^{n-1} f).$$

More generally, for $n > 1$ and $f: \mathcal{X}^n \rightarrow \mathbb{R}$,

$$E(f(X_{1:n})) = E(g(X_{1:n-1})) \quad ,$$

with

$$g: \mathcal{X}^{n-1} \rightarrow \mathbb{R}: x_{1:n-1} \mapsto E_{q_{x_{n-1}}} (f(x_{1:n-1} \bullet)).$$

Global expectations via the transition operator

We've essentially shown that for all $n > 1$ and $f: \mathcal{X} \rightarrow \mathbb{R}$,

$$E(f(X_n)) = E_{\pi_1}(\mathbb{T}^{n-1}f)$$

More generally, for $n > 1$ and $f: \mathcal{X}^n \rightarrow \mathbb{R}$,

$$E(f(X_{1:n})) = E(g(X_{1:n-1})) = E([\mathbb{T}f(X_{1:n-1}\bullet)](X_{n-1})),$$

since for all $x_{1:n-1} \in \mathcal{X}^{n-1}$,

$$g(x_{1:n-1}) = E_{q_{x_{n-1}}}(f(x_{1:n-1}\bullet)) = [\mathbb{T}f(x_{1:n-1}\bullet)](x_{n-1}).$$

The transition operator

Let $T: \mathbb{R}^{\mathcal{X}} \rightarrow \mathbb{R}^{\mathcal{X}}$ be the corresponding *transition operator* which maps $f: \mathcal{X} \rightarrow \mathbb{R}$ to

$$Tf: \mathcal{X} \rightarrow \mathbb{R}: x \mapsto E_{q_x}(f) = \sum_{y \in \mathcal{X}} q_x(y) f(y).$$

For some ordering x_1, \dots, x_m of \mathcal{X} and with basis $\mathcal{B} = \{\mathbb{I}_{x_1}, \dots, \mathbb{I}_{x_m}\}$, the transition operator T has the matrix representation

$$T = [T]_{\mathcal{B}, \mathcal{B}} = \begin{bmatrix} q_{x_1}(x_1) & \cdots & q_{x_1}(x_m) \\ \vdots & \ddots & \vdots \\ q_{x_m}(x_1) & \cdots & q_{x_m}(x_m) \end{bmatrix}.$$

Global expectations via the transition operator

We've essentially shown that for all $n > 1$ and $f: \mathcal{X} \rightarrow \mathbb{R}$,

$$E(f(X_n)) = E_{\pi_1}(\mathbf{T}^{n-1}f) = [\pi_1]_{\mathcal{B}}^{\top} T^{n-1} [f]_{\mathcal{B}},$$

with

$$[\pi_1]_{\mathcal{B}}^{\top} = [\pi_1(x_1) \quad \cdots \quad \pi_1(x_m)] \quad \text{and} \quad [f]_{\mathcal{B}} = \begin{bmatrix} f(x_1) \\ \vdots \\ f(x_m) \end{bmatrix}.$$

Exercise 1

For $\mathcal{X} = \{\mathbf{a}, \mathbf{b}\}$, $\pi_1 = \mathbb{I}_{\mathbf{a}}$, $[q_{\mathbf{a}}]_{\mathcal{B}} = [\alpha \quad 1 - \alpha]^{\top}$ and $[q_{\mathbf{b}}]_{\mathcal{B}} = [1 - \beta \quad \beta]^{\top}$, determine

$$P(X_3 = \mathbf{b}) = E(\mathbb{I}_{\mathbf{b}}(X_3)).$$

Exercise 1

For $\mathcal{X} = \{\mathbf{a}, \mathbf{b}\}$, $\pi_1 = \mathbb{I}_{\mathbf{a}}$, $[q_{\mathbf{a}}]_{\mathcal{B}} = [\alpha \quad 1 - \alpha]^{\top}$ and $[q_{\mathbf{b}}]_{\mathcal{B}} = [1 - \beta \quad \beta]^{\top}$,

$$\begin{aligned} P(X_3 = \mathbf{b}) &= E(\mathbb{I}_{\mathbf{b}}(X_3)) \\ &= [\pi_1]_{\mathcal{B}}^{\top} T^2 [\mathbb{I}_{\mathbf{b}}]_{\mathcal{B}} \end{aligned}$$

Exercise 1

For $\mathcal{X} = \{\mathbf{a}, \mathbf{b}\}$, $\pi_1 = \mathbb{I}_{\mathbf{a}}$, $[q_{\mathbf{a}}]_{\mathcal{B}} = [\alpha \quad 1 - \alpha]^{\top}$ and $[q_{\mathbf{b}}]_{\mathcal{B}} = [1 - \beta \quad \beta]^{\top}$,

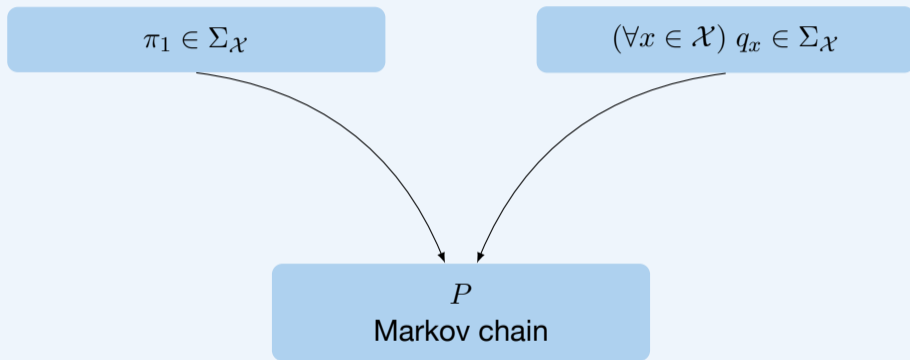
$$\begin{aligned} P(X_3 = \mathbf{b}) &= E(\mathbb{I}_{\mathbf{b}}(X_3)) \\ &= [\pi_1]_{\mathcal{B}}^{\top} T^2 [q_{\mathbf{b}}]_{\mathcal{B}} \\ &= [1 \quad 0] \begin{bmatrix} \alpha & 1 - \alpha \\ 1 - \beta & \beta \end{bmatrix}^2 \begin{bmatrix} 0 \\ 1 \end{bmatrix} \end{aligned}$$

Exercise 1

For $\mathcal{X} = \{\mathbf{a}, \mathbf{b}\}$, $\pi_1 = \mathbb{I}_{\mathbf{a}}$, $[q_{\mathbf{a}}]_{\mathcal{B}} = [\alpha \quad 1 - \alpha]^{\top}$ and $[q_{\mathbf{b}}]_{\mathcal{B}} = [1 - \beta \quad \beta]^{\top}$,

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Markov chain



Markov chain

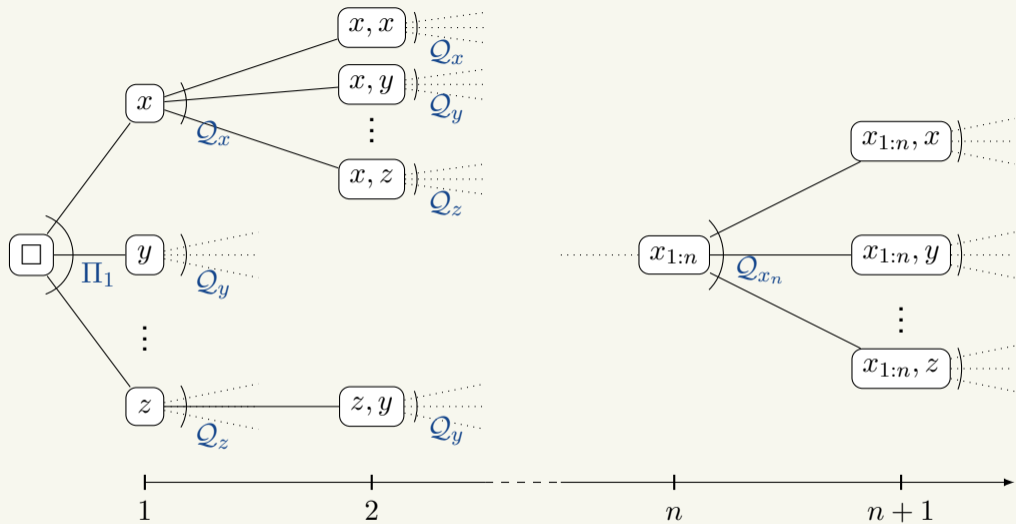
$$\pi_1 \in \Sigma_{\mathcal{X}}$$

$$(\forall x \in \mathcal{X}) q_x \in \Sigma_{\mathcal{X}}$$

What if we do not know the local pmfs π_1 & q . precisely?

P
Markov chain





Imprecise Markov chain

$$\Pi_1 \subseteq \Sigma_{\mathcal{X}}$$

$$(\forall x \in \mathcal{X}) Q_x \subseteq \Sigma_{\mathcal{X}}$$



Imprecise Markov chain

$$\Pi_1 \subseteq \Sigma_{\mathcal{X}}$$

$$(\forall x \in \mathcal{X}) \mathcal{Q}_x \subseteq \Sigma_{\mathcal{X}}$$

Markov chain P is **compatible** if $\pi_1 \in \Pi_1$ and $(\forall x \in \mathcal{X}) q_x \in \mathcal{Q}_x$

$$\mathcal{P}^M$$

all compatible
Markov chains

Upper expectations

For $n \in \mathbb{N}$ and $f: \mathcal{X}^n \rightarrow \mathbb{R}$,

$$\bar{E}^M(f(X_{1:n})) := \sup_{P \in \mathcal{P}^M} E_P(f(X_{1:n})).$$

Upper expectations

For $n \in \mathbb{N}$ and $f: \mathcal{X}^n \rightarrow \mathbb{R}$,

$$\bar{E}^{\mathbb{M}}(f(X_{1:n})) := \sup_{P \in \mathcal{P}^{\mathbb{M}}} E_P(f(X_{1:n})).$$

In particular, for $n > 1$ and $f: \mathcal{X} \rightarrow \mathbb{R}$,

$$\begin{aligned} \bar{E}^{\mathbb{M}}(f(X_n)) &= \sup_{P \in \mathcal{P}^{\mathbb{M}}} E_P(f(X_n)) \\ &= \sup_{P \in \mathcal{P}^{\mathbb{M}}} E_{\pi_1}(\mathbb{T}^{n-1}f). \end{aligned}$$

Exercise 2

Again consider $\mathcal{X} = \{a, b\}$, but now with $\Pi_1 = \{\mathbb{I}_a\}$,

$$\mathcal{Q}_a = \{\alpha \mathbb{I}_a + (1 - \alpha) \mathbb{I}_b : \alpha \in [\underline{\alpha}, \bar{\alpha}]\} \quad \text{and} \quad \mathcal{Q}_b = \{(1 - \beta) \mathbb{I}_a + \beta \mathbb{I}_b : \beta \in [\underline{\beta}, \bar{\beta}]\},$$

where $\underline{\alpha} = 2/5$, $\bar{\alpha} = 3/5$, $\underline{\beta} = 1/3$ and $\bar{\beta} = 1/2$. Determine

$$\bar{E}^M(\mathbb{I}_b(X_3)).$$

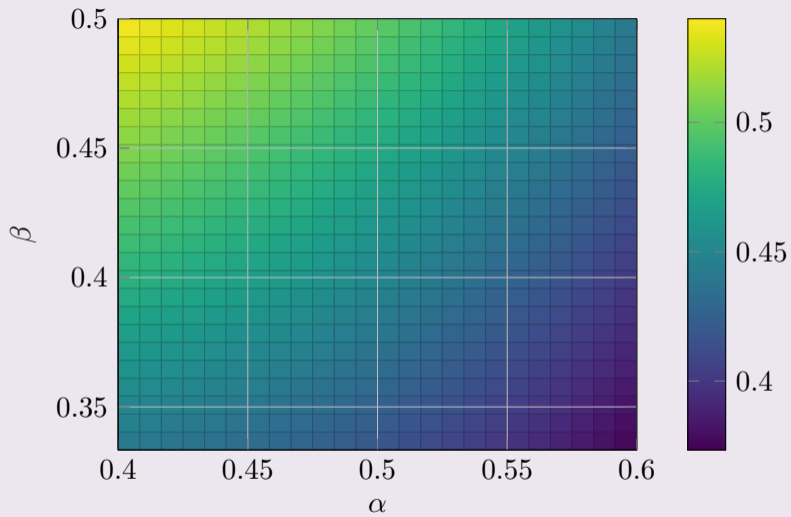
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where $\underline{\alpha} = 2/5$, $\bar{\alpha} = 3/5$, $\underline{\beta} = 1/3$ and $\bar{\beta} = 1/2$. Then

$$\bar{E}^M(\mathbb{I}_b(X_3)) = \sup_{P \in \mathcal{P}^M} E_P(\mathbb{I}_b(X_3)) = \sup_{P \in \mathcal{P}^M} \alpha(1 - \alpha) + (1 - \alpha)\beta.$$



Exercise 2

Again consider $\mathcal{X} = \{a, b\}$, but now with $\Pi_1 = \{\mathbb{I}_a\}$,

$$\mathcal{Q}_a = \{\alpha\mathbb{I}_a + (1 - \alpha)\mathbb{I}_b : \alpha \in [\underline{\alpha}, \bar{\alpha}]\} \quad \text{and} \quad \mathcal{Q}_b = \{(1 - \beta)\mathbb{I}_a + \beta\mathbb{I}_b : \beta \in [\underline{\beta}, \bar{\beta}]\},$$

where $\underline{\alpha} = 2/5$, $\bar{\alpha} = 3/5$, $\underline{\beta} = 1/3$ and $\bar{\beta} = 1/2$. Then

$$\bar{E}^M(\mathbb{I}_b(X_3)) = \sup_{P \in \mathcal{P}^M} E_P(\mathbb{I}_b(X_3)) = \sup_{P \in \mathcal{P}^M} \alpha(1 - \alpha) + (1 - \alpha)\beta = \frac{27}{50}.$$

Exercise 2

Again consider $\mathcal{X} = \{a, b\}$, but now with $\Pi_1 = \{\mathbb{I}_a\}$,

$$\mathcal{Q}_a = \{\alpha\mathbb{I}_a + (1 - \alpha)\mathbb{I}_b : \alpha \in [\underline{\alpha}, \bar{\alpha}]\} \quad \text{and} \quad \mathcal{Q}_b = \{(1 - \beta)\mathbb{I}_a + \beta\mathbb{I}_b : \beta \in [\underline{\beta}, \bar{\beta}]\},$$

where $\underline{\alpha} = 2/5$, $\bar{\alpha} = 3/5$, $\underline{\beta} = 1/3$ and $\bar{\beta} = 1/2$. Then

$$\bar{E}^M(\mathbb{I}_b(X_3)) = \sup_{P \in \mathcal{P}^M} E_P(\mathbb{I}_b(X_3)) = \sup_{P \in \mathcal{P}^M} \alpha(1 - \alpha) + (1 - \alpha)\beta = \frac{27}{50}.$$



Imprecise Markov chain

$$\Pi_1 \subseteq \Sigma_{\mathcal{X}}$$

$$(\forall x \in \mathcal{X}) \mathcal{Q}_x \subseteq \Sigma_{\mathcal{X}}$$

Markov chain P is **compatible** if $\pi_1 \in \Pi_1$ and $(\forall x \in \mathcal{X}) q_x \in \mathcal{Q}_x$

$$\mathcal{P}^M$$

all compatible
Markov chains

Imprecise Markov chains

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$$(\forall x \in \mathcal{X}) \mathcal{Q}_x \subseteq \Sigma_{\mathcal{X}}$$

P is **compatible** if $\pi_1 \in \Pi_1$ and $(\forall n \in \mathbb{N}, x_{1:n} \in \mathcal{X}^n) q_{x_{1:n}} \in \mathcal{Q}_{x_n}$

\mathcal{P}^M
all compatible
Markov chains

\subseteq

\mathcal{P}
all compatible
probability trees

Imprecise Markov chains

$$\Pi_1 \subseteq \Sigma_{\mathcal{X}}$$

$$(\forall x \in \mathcal{X}) \mathcal{Q}_x \subseteq \Sigma_{\mathcal{X}}$$

P is **compatible** if $\pi_1 \in \Pi_1$ and $(\forall n \in \mathbb{N}, x_{1:n} \in \mathcal{X}^n) q_{x_{1:n}} \in \mathcal{Q}_{x_n}$

\mathcal{P}^M
all compatible
Markov chains

\subseteq

\mathcal{P}
all compatible
probability trees

\overline{E}^M

\leq

\overline{E}

Exercise 3

As before consider $\mathcal{X} = \{a, b\}$, $\Pi_1 = \{\mathbb{I}_a\}$,

$$Q_a = \{\alpha \mathbb{I}_a + (1 - \alpha) \mathbb{I}_b : \alpha \in [\underline{\alpha}, \bar{\alpha}]\} \quad \text{and} \quad Q_b = \{(1 - \beta) \mathbb{I}_a + \beta \mathbb{I}_b : \beta \in [\underline{\beta}, \bar{\beta}]\}$$

with $\underline{\alpha} = 2/5$, $\bar{\alpha} = 3/5$, $\underline{\beta} = 1/3$ and $\bar{\beta} = 1/2$. Determine

$$\bar{E}(\mathbb{I}_b(X_3)).$$

Exercise 3

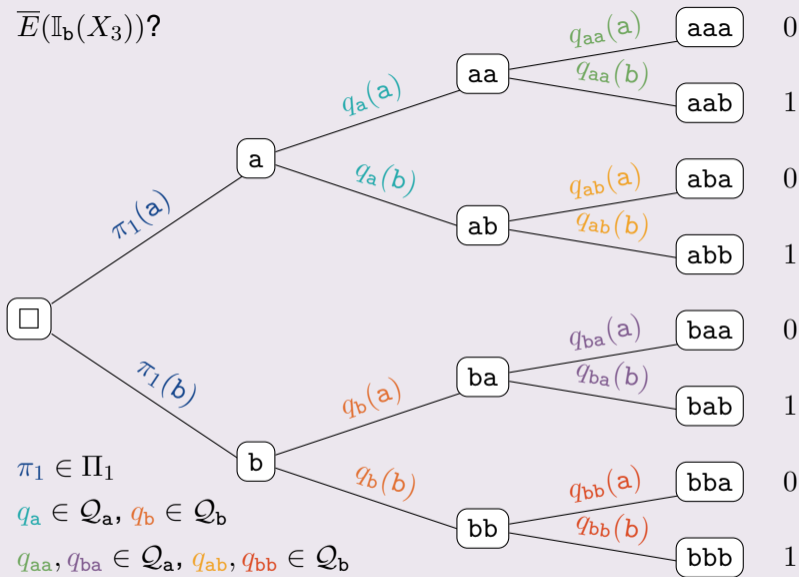
As before consider $\mathcal{X} = \{a, b\}$, $\Pi_1 = \{\mathbb{I}_a\}$,

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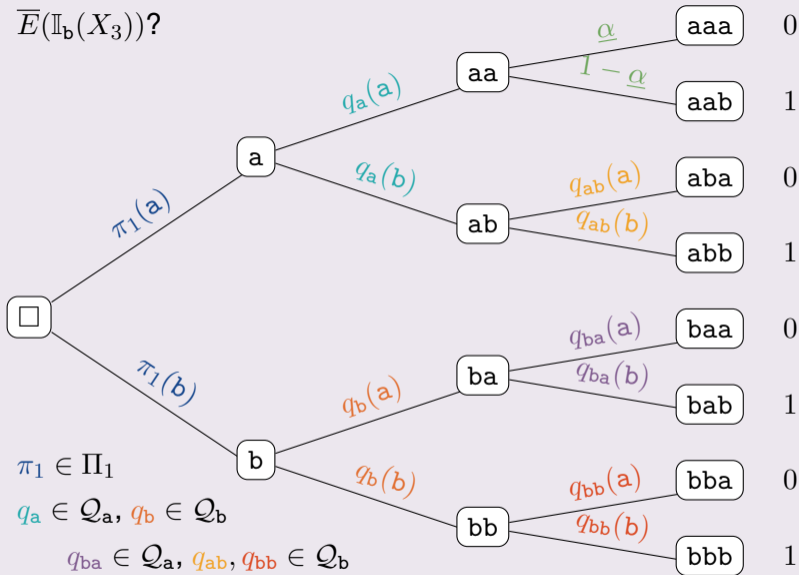
with $\underline{\alpha} = 2/5$, $\bar{\alpha} = 3/5$, $\underline{\beta} = 1/3$ and $\bar{\beta} = 1/2$. Then

$$\bar{E}(\mathbb{I}_b(X_3)) = \sup_{P \in \mathcal{P}} E_P(\mathbb{I}_b(X_3)).$$

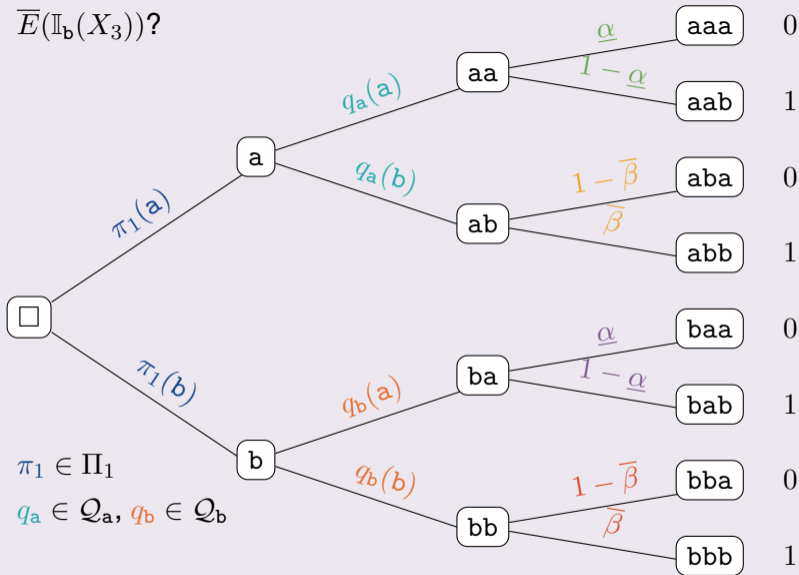
$\bar{E}(\mathbb{I}_b(X_3))?$



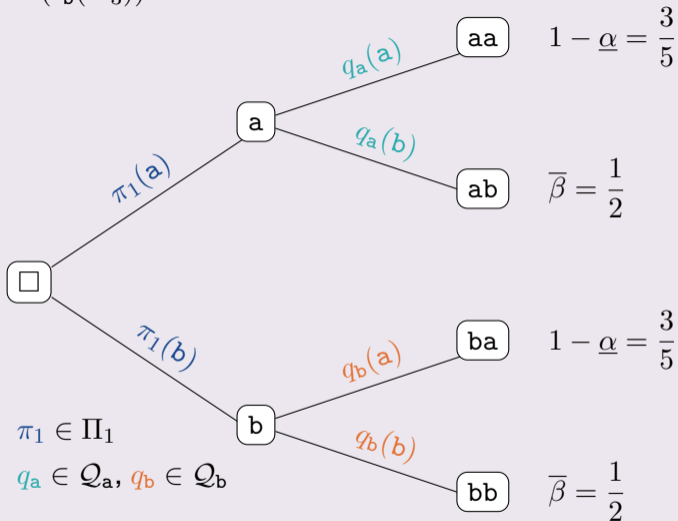
$\bar{E}(\mathbb{I}_b(X_3))?$



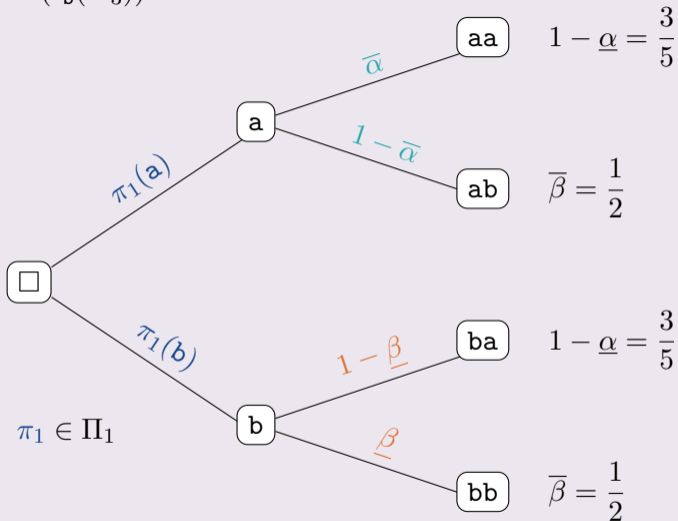
$\bar{E}(\mathbb{I}_b(X_3))?$



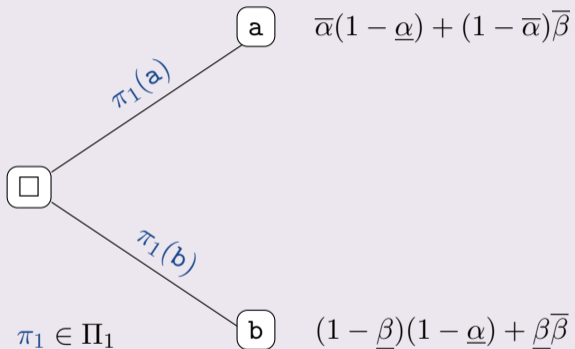
$\bar{E}(\mathbb{I}_b(X_3))?$



$\bar{E}(\mathbb{I}_b(X_3))?$



$\bar{E}(\mathbb{I}_b(X_3))?$



$$\bar{E}(\mathbb{I}_{\mathbf{b}}(X_3))?$$

$$\boxed{\square} \quad \bar{E}(\mathbb{I}_{\mathbf{b}}(X_3)) = \bar{\alpha}(1 - \underline{\alpha}) + (1 - \bar{\alpha})\bar{\beta} = \frac{28}{50}$$

Exercise 3

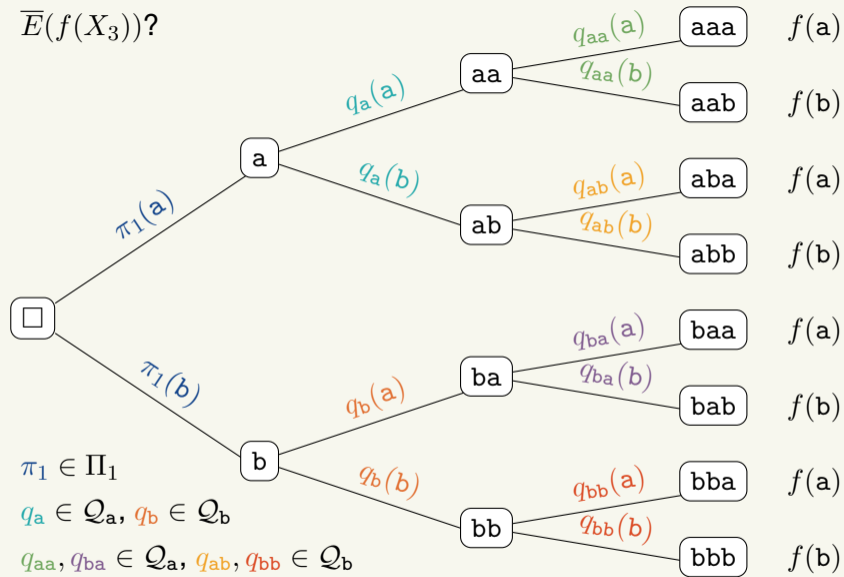
As before consider $\mathcal{X} = \{a, b\}$, $\Pi_1 = \{\mathbb{I}_a\}$,

$$Q_a = \{\alpha \mathbb{I}_a + (1 - \alpha) \mathbb{I}_b : \alpha \in [\underline{\alpha}, \bar{\alpha}]\} \quad \text{and} \quad Q_b = \{(1 - \beta) \mathbb{I}_a + \beta \mathbb{I}_b : \beta \in [\underline{\beta}, \bar{\beta}]\}$$

with $\underline{\alpha} = 2/5$, $\bar{\alpha} = 3/5$, $\underline{\beta} = 1/3$ and $\bar{\beta} = 1/2$. Then

$$\bar{E}(\mathbb{I}_b(X_3)) = \frac{28}{50} > \frac{27}{50} = \bar{E}^M(\mathbb{I}_b(X_3))!$$

$\overline{E}(f(X_3))?$



The upper transition operator

Let $\bar{T}: \mathbb{R}^{\mathcal{X}} \rightarrow \mathbb{R}^{\mathcal{X}}$ be the operator which maps $f: \mathcal{X} \rightarrow \mathbb{R}$ to

$$\bar{T}f: \mathcal{X} \rightarrow \mathbb{R}: x \mapsto \bar{E}_{Q_x}(f) = \sup_{q \in Q_x} \sum_{y \in \mathcal{X}} q(y) f(y).$$

The upper transition operator

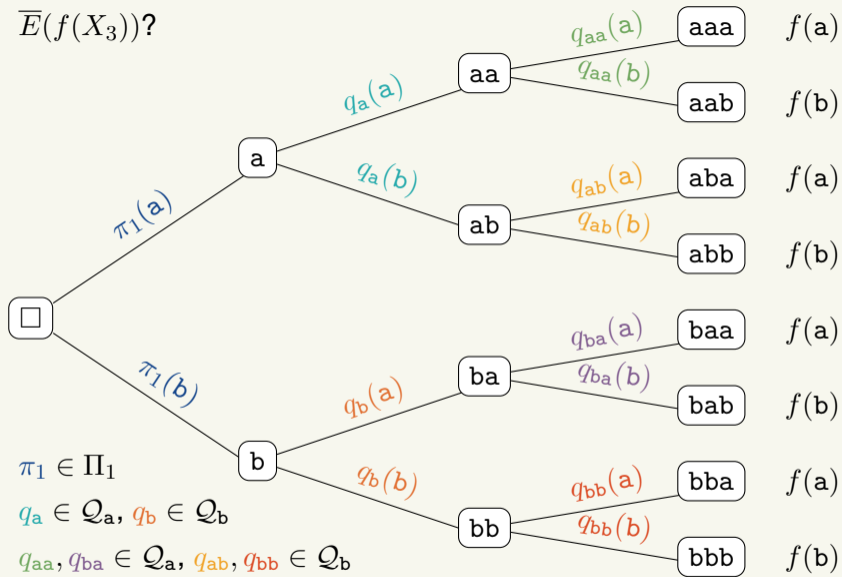
Let $\bar{T}: \mathbb{R}^{\mathcal{X}} \rightarrow \mathbb{R}^{\mathcal{X}}$ be the operator which maps $f: \mathcal{X} \rightarrow \mathbb{R}$ to

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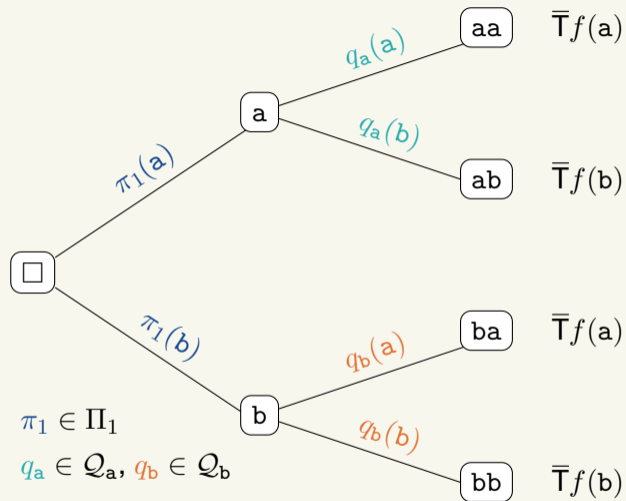
This is an example of an *upper transition operator*: an operator $\bar{S}: \mathbb{R}^{\mathcal{X}} \rightarrow \mathbb{R}^{\mathcal{X}}$ such that

1. $\bar{S}f \leq \sup f$ for all $f \in \mathbb{R}^{\mathcal{X}}$;
2. $\bar{S}(f + g) \leq \bar{S}f + \bar{S}g$ for all $f, g \in \mathbb{R}^{\mathcal{X}}$;
3. $\bar{S}(\lambda f) = \lambda \bar{S}f$ for all $\lambda \in \mathbb{R}_{\geq 0}$, $f \in \mathbb{R}^{\mathcal{X}}$.

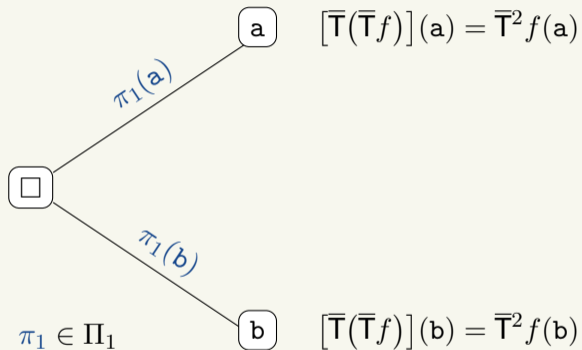
$\overline{E}(f(X_3))?$



$\bar{E}(f(X_3))?$



$\overline{E}(f(X_3))?$



$$\bar{E}(f(X_3))?$$

$$\boxed{\square} \quad \bar{E}(f(X_3)) = \bar{E}_{\Pi_1}(\bar{T}^2 f)$$

Upper expectations

In essence, we've shown that for all $n > 1$ and $f: \mathcal{X} \rightarrow \mathbb{R}$,

$$\bar{E}(f(X_n)) = \bar{E}_{\Pi_1}(\bar{T}^{n-1}f).$$

Upper expectations

In essence, we've shown that for all $n > 1$ and $f: \mathcal{X} \rightarrow \mathbb{R}$,

$$\bar{E}(f(X_n)) = \bar{E}_{\Pi_1}(\bar{T}^{n-1}f).$$

More generally, it has been shown that for all $n > 1$ and $f: \mathcal{X}^n \rightarrow \mathbb{R}$,

$$\bar{E}(f(X_{1:n})) = \bar{E}([\bar{T}f(X_{1:n-1}, \bullet)](X_{n-1})).$$

Imprecise Markov chains

$$\Pi_1 \subseteq \Sigma_{\mathcal{X}}$$

$$(\forall x \in \mathcal{X}) \mathcal{Q}_x \subseteq \Sigma_{\mathcal{X}}$$

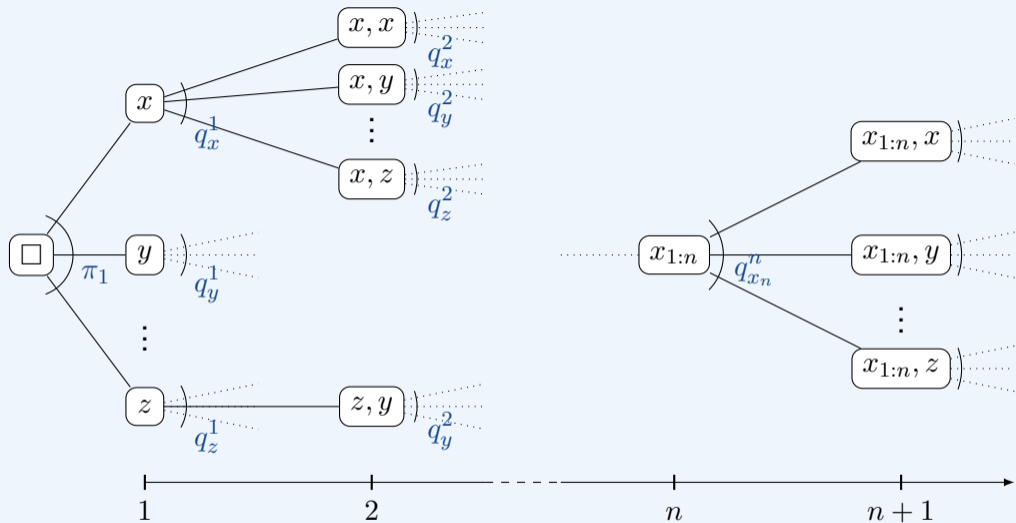
P is **compatible** if $\pi_1 \in \Pi_1$ and $(\forall n \in \mathbb{N}, x_{1:n} \in \mathcal{X}^n) q_{x_{1:n}} \in \mathcal{Q}_{x_n}$

 \mathcal{P}^M

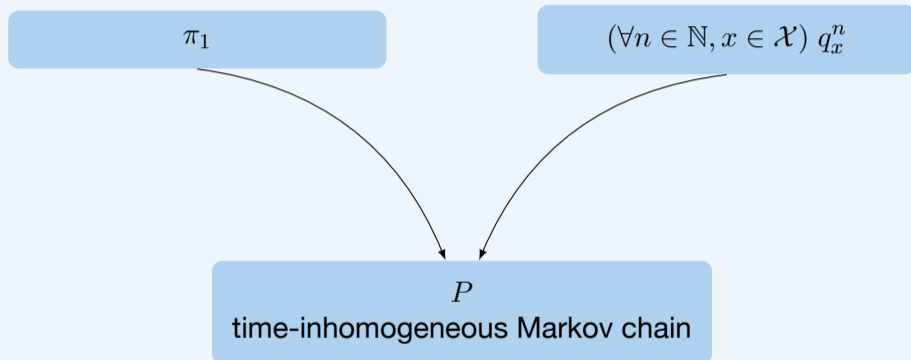
all compatible
Markov chains

 \subseteq \mathcal{P}

all compatible
probability trees



Time-inhomogeneous Markov chain



Imprecise Markov chains

$$\Pi_1 \subseteq \Sigma_{\mathcal{X}}$$

$$(\forall x \in \mathcal{X}) \mathcal{Q}_x \subseteq \Sigma_{\mathcal{X}}$$

P is **compatible** if $\pi_1 \in \Pi_1$ and $(\forall n \in \mathbb{N}, x_{1:n} \in \mathcal{X}^n) q_{x_{1:n}} \in \mathcal{Q}_{x_n}$

 \mathcal{P}^M

all compatible
Markov chains

 \subseteq \mathcal{P}^{IM}

all compatible (time-)
inhomogeneous Markov chains

 \subseteq \mathcal{P}

all compatible
probability trees

 \overline{E}^M \leq \overline{E}^{IM} \leq \overline{E}

Imprecise Markov chains

$$\Pi_1 \subseteq \Sigma_{\mathcal{X}}$$

$$(\forall x \in \mathcal{X}) \mathcal{Q}_x \subseteq \Sigma_{\mathcal{X}}$$

P is **compatible** if $\pi_1 \in \Pi_1$ and $(\forall n \in \mathbb{N}, x_{1:n} \in \mathcal{X}^n) q_{x_{1:n}} \in \mathcal{Q}_{x_n}$

 \mathcal{P}^M

all compatible
Markov chains

 \subseteq \mathcal{P}^{IM}

all compatible (time-)
inhomogeneous Markov chains

 \subseteq \mathcal{P}

all compatible
probability trees

 \overline{E}^M \leq \overline{E}^{IM}  \leq \overline{E}

Exercise 4

Verify that for all $f: \mathcal{X} \rightarrow \mathbb{R}$,

$$\bar{E}^{\mathbb{M}}(f(X_1)) = \bar{E}^{\text{IM}}(f(X_1)) = \bar{E}(f(X_1)).$$

Is it true that for all $n \in \mathbb{N}$ and $f: \mathcal{X} \rightarrow \mathbb{R}$,

$$\bar{E}^{\text{IM}}(f(X_{n+1})) = \bar{E}_{\Pi_1}(\bar{\mathbb{T}}^n f) = \bar{E}(f(X_{n+1}))?$$

More generally, is it true that for all $n > 1$ and $f: \mathcal{X}^n \rightarrow \mathbb{R}$,

$$\bar{E}^{\text{IM}}(f(X_{1:n})) = \bar{E}^{\text{IM}}([\bar{\mathbb{T}}f(X_{1:n-1}, \bullet)](X_{n-1}))?$$

Imprecise Markov chains

$$\Pi_1 \subseteq \Sigma_{\mathcal{X}}$$

$$(\forall x \in \mathcal{X}) \mathcal{Q}_x \subseteq \Sigma_{\mathcal{X}}$$

Imprecise Markov chains

$$\Pi_1 \subseteq \Sigma_{\mathcal{X}}$$



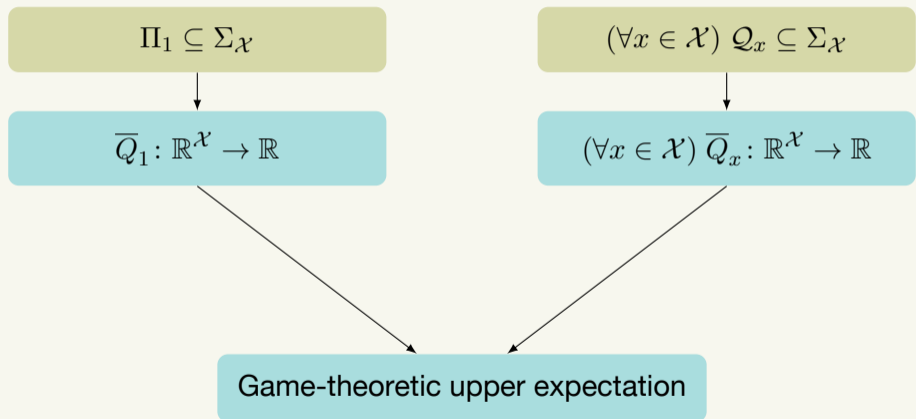
$$\bar{Q}_1: \mathbb{R}^{\mathcal{X}} \rightarrow \mathbb{R}$$

$$(\forall x \in \mathcal{X}) Q_x \subseteq \Sigma_{\mathcal{X}}$$



$$(\forall x \in \mathcal{X}) \bar{Q}_x: \mathbb{R}^{\mathcal{X}} \rightarrow \mathbb{R}$$

Imprecise Markov chains



Imprecise Markov chains

$$\Pi_1 \subseteq \Sigma_{\mathcal{X}}$$



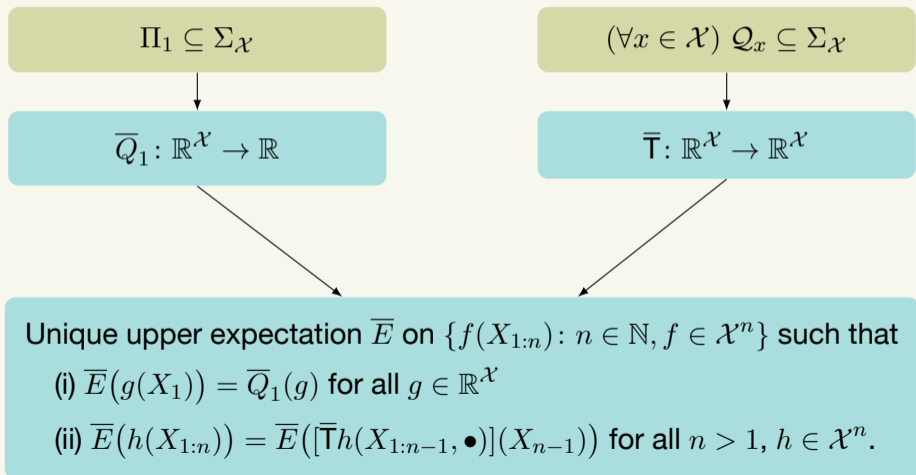
$$\bar{Q}_1: \mathbb{R}^{\mathcal{X}} \rightarrow \mathbb{R}$$

$$(\forall x \in \mathcal{X}) Q_x \subseteq \Sigma_{\mathcal{X}}$$



$$\bar{T}: \mathbb{R}^{\mathcal{X}} \rightarrow \mathbb{R}^{\mathcal{X}}$$

Imprecise Markov chains



Ergodicity

A transition operator T is *ergodic* if for all $f: \mathcal{X} \rightarrow \mathbb{R}$, $T^n f$ converges to a constant function as $n \rightarrow \infty$.

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In that case, for any $\pi_1 \in \Sigma_{\mathcal{X}}$,

$$E(f(X_n)) = E_{\pi_1}(T^{n-1}f)$$

converges to this constant value as $n \rightarrow \infty$.

Necessary and sufficient conditions for ergodicity are well-known.

Ergodicity

An upper transition operator \bar{T} is *ergodic* if for all $f: \mathcal{X} \rightarrow \mathbb{R}$, $\bar{T}^n f$ converges to a constant function as $n \rightarrow \infty$.

In that case, for any $\Pi_1 \subseteq \Sigma_{\mathcal{X}}$,

$$\bar{E}(f(X_n)) = \bar{E}_{\Pi_1}(\bar{T}^{n-1} f)$$

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Ergodicity

An upper transition operator \bar{T} is *ergodic* if for all $f: \mathcal{X} \rightarrow \mathbb{R}$, $\bar{T}^n f$ converges to a constant function as $n \rightarrow \infty$.

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$$\bar{E}(f(X_n)) = \bar{E}_{\Pi_1}(\bar{T}^{n-1} f)$$

converges to this constant value as $n \rightarrow \infty$.

Necessary and sufficient conditions for ergodicity have been studied,
but the aim of the project is to **rediscover** them!

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