

# Lebesgue's Convergence Theorem and Fatou's Lemma for Varying Probabilities

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Innovative Research in Mathematical Finance  
Conference in Honor of Yuri Kabanov

Marseille, France  
September 7, 2018

This talk is based on joint papers with Pavlo Kasyanov and Yan Liang.

# Plan of the Talk

1. Classic facts
2. Fatou's lemma for varying probabilities including uniform Fatou's lemma
3. Lebesgue's convergence theorem for varying probabilities
4. Applications

# Fatou's Lemma: Classic Facts

1. Fatou's lemma
2. Lebesgue's dominated convergence theorem
3. Monotone convergence theorem

## Fatou's Lemma

For a probability measure  $p$  and a sequence of measurable functions, the inequality

$$\liminf_{n \rightarrow \infty} \int f_n(x) p(dx) \geq \int \liminf_{n \rightarrow \infty} f_n(x) p(dx)$$

holds, if one of the following conditions is satisfied:

- (i) each function  $f_n$  is nonnegative;
- (ii) there exists a measurable function  $g$  such that  $g \leq f_n$  and  $\int g(x) p(dx) > -\infty$ ;
- (iii) the sequence  $\{f_n^-\}$ , where  $f_n^- := -\min\{f_n, 0\}$ , is **uniformly integrable**, that is,

$$\lim_{K \rightarrow +\infty} \inf_{n=1,2,\dots} \int_{\mathbb{X}} f_n(x) \mathbf{I}\{x \in \mathbb{X} : f_n(x) \leq -K\} p(dx) \geq 0.$$

Stronger results hold when the sequence of functions satisfies some additional conditions. Lebesgue's dominated convergence theorem and monotone convergence theorem are corollaries from **Fatou's lemma**.

# Extensions of Fatou's lemma

- A. Fatou's lemma for converging probabilities (weak convergence, setwise convergence, convergence in total variation)
- B. Uniform Fatou's lemma
- C. Lower bounds on possibly negative functions
  - (i) existence of a sequence of minorant functions
  - (ii) uniform integrability with respect to a sequence of probability measures
- D. Convergence and continuity properties of functions
  - (i) lower semi-equicontinuity
  - (ii) semi-convergence in probability

# Convergence of Probabilities

We are interested in the situation when there is a sequence of **converging probabilities** on a metric space  $\mathbb{X}$ . Recall the definition of the following three types of convergence:

(i) *weak convergence (convergence in probability)*

$p_n \rightarrow p$  if for every **bounded continuous function**  $f$

$$\int f(x)p_n(dx) \rightarrow \int f(x)p(dx) \quad (1)$$

(ii) *setwise convergence*

$p_n \rightarrow p$  if  $p_n(E) \rightarrow p(E)$  for each **measurable subset**  $E$ . Equivalently, (1) holds for every **bounded measurable function**  $f$ .

(iii) *convergence in total variation*

$p_n \rightarrow p$  if  $\rho_{TV}(p, p_n) \rightarrow 0$ , where  $\rho_{TV}(p, p_n) = 2 \sup\{|p(B) - p_n(B)| : B \in \mathcal{B}(\mathbb{X})\}$ .

For discrete random variables, these three types of convergence coincide.

**Weak convergence** is the most natural and general form of convergence of probabilities,

(iii)  $\Rightarrow$  (ii)  $\Rightarrow$  (i).

# Fatou's Lemma for Varying Probabilities

*Theorem (Serfozo 1981)*

For probabilities **converging weakly**  $p_n \rightarrow p$  and nonnegative measurable functions  $f_n$ ,

$$\liminf_{n \rightarrow \infty} \int f_n(x) p_n(dx) \geq \int \liminf_{y \rightarrow x, n \rightarrow \infty} f_n(y) p(dx).$$

*Theorem (Royden 1963)*

For probabilities **converging setwise**  $p_n \rightarrow p$  and nonnegative measurable functions  $f_n$ ,

$$\liminf_{n \rightarrow \infty} \int f_n(x) p_n(dx) \geq \int \liminf_{n \rightarrow \infty} f_n(x) p(dx).$$

# Uniform Fatou's Lemma

Let  $(\mathbb{X}, \mathcal{F})$  be a measurable space. The inequality in Fatou's lemma can be rewritten as

$$\inf_{X \in \mathcal{F}} \left\{ \liminf_{n \rightarrow \infty} \int_X f_n(x) p_n(dx) - \int_X [\liminf_{n \rightarrow \infty} f_n(x)] p(dx) \right\} \geq 0. \quad (2)$$

Uniform Fatou's lemma (F., Kasyanov, and Zgurovsky 2016) is a stronger inequality:

$$\liminf_{n \rightarrow \infty} \inf_{X \in \mathcal{F}} \left\{ \int_X f_n(x) p_n(dx) - \int_X [\liminf_{n \rightarrow \infty} f_n(x)] p(dx) \right\} \geq 0. \quad (3)$$

This is a stronger inequality and examples support this.

The difference between (2) and (3) is similar to the difference between convergence and uniform convergence.

# Uniform Fatou's Lemma

*Uniform Fatou's Lemma (F., Kasyanov, and Zgurovsky 2016)*

Let  $(\mathbb{X}, \mathcal{F})$  be a measurable space, a sequence of probability measures  $\{p_n\}_{n=1,2,\dots}$  converge in total variation to a probability measure  $p$  on  $\mathbb{X}$ ,  $f \in L^1(\mathbb{X}; p)$ , and  $f_n \in L^1(\mathbb{X}; p_n)$  for each  $n = 1, 2, \dots$ . Then the inequality

$$\liminf_{n \rightarrow \infty} \inf_{X \in \mathcal{F}} \left( \int_X f_n(x) p_n(dx) - \int_X f(x) p(dx) \right) \geq 0$$

holds if and only if the following two statements hold:

(i) for each  $\epsilon > 0$

$$p(\{x \in \mathbb{X} : f_n(x) \leq f(x) - \epsilon\}) \rightarrow 0 \text{ as } n \rightarrow \infty,$$

and, therefore, there exists a subsequence  $\{f_{n_k}\}_{k=1,2,\dots} \subseteq \{f_n\}_{n=1,2,\dots}$  such that

$$\liminf_{k \rightarrow \infty} f_{n_k}(x) \geq f(x) \quad \text{for } p\text{-a.s. } x \in \mathbb{X};$$

(ii) the following inequality holds:

$$\lim_{K \rightarrow +\infty} \inf_{n=1,2,\dots} \int_{\mathbb{X}} f_n(x) \mathbf{I}\{x \in \mathbb{X} : f_n(x) \leq -K\} p_n(dx) \geq 0.$$

Observation: As a special case, uniform Fatou's lemma holds for

$$f(x) := \liminf_{n \rightarrow \infty} f_n(x).$$



# Uniform Lebesgue's Convergence Theorem

*Uniform Lebesgue's Convergence Theorem (F., Kasyanov, and Zgurovsky 2016)*

Let  $(\mathbb{X}, \mathcal{F})$  be a measurable space, a sequence of probability measures  $\{p_n\}_{n=1,2,\dots}$  converge in total variation to a probability measure  $p$  on  $\mathbb{X}$ ,  $f \in L^1(\mathbb{X}; p)$ , and  $f_n \in L^1(\mathbb{X}; p_n)$  for each  $n = 1, 2, \dots$ . Then the equality

$$\lim_{n \rightarrow \infty} \sup_{X \in \mathcal{F}} \left| \int_X f_n(x) p_n(dx) - \int_X f(x) p(dx) \right| = 0$$

holds if and only if the following two statements hold:

- (i) the sequence of functions  $\{f_n\}_{n=1,2,\dots}$  converges in probability  $p$  to  $f$ ; and
- (ii)

$$\lim_{K \rightarrow +\infty} \sup_{n=1,2,\dots} \int |f_n(x)| \mathbf{I}\{x \in \mathbb{X} : |f_n(x)| \geq K\} p_n(dx) = 0.$$

# Uniform Integrability of a Sequence of Functions

*Uniformly integrable (u.i.) with respect to (w.r.t.)  $\{p_n\}$*

$$\lim_{K \rightarrow +\infty} \sup_{n=1,2,\dots} \int |f_n(x)| \mathbf{I}\{x \in \mathbb{X} : |f_n(x)| \geq K\} p_n(dx) = 0.$$

*Asymptotically uniformly integrable (a.u.i.) w.r.t.  $\{p_n\}$*

$$\lim_{K \rightarrow +\infty} \limsup_{n \rightarrow \infty} \int |f_n(x)| \mathbf{I}\{x \in \mathbb{X} : |f_n(x)| \geq K\} p_n(dx) = 0.$$

## *Theorem*

*A sequence of functions  $\{f_n\}_{n=1,2,\dots}$  is a.u.i. w.r.t.  $\{p_n\}_{n=1,2,\dots}$  if and only if there exists  $\tilde{N} = 0, 1, 2, \dots$  such that  $\{f_{n+\tilde{N}}\}_{n=1,2,\dots}$  is u.i. w.r.t.  $\{p_{n+\tilde{N}}\}_{n=1,2,\dots}$  (Kartashov 2008 for  $p_n = p$ ).*

# Uniform Fatou's Lemma

*Uniform Fatou's Lemma (F., Kasyanov, and Zgurovsky 2016)*

Let  $(\mathbb{X}, \mathcal{F})$  be a measurable space, a sequence of probability measures  $\{p_n\}_{n=1,2,\dots}$  converge in total variation to a probability measure  $p$  on  $\mathbb{X}$ ,  $f \in L^1(\mathbb{X}; p)$ , and  $f_n \in L^1(\mathbb{X}; p_n)$  for each  $n = 1, 2, \dots$ . Then the inequality

$$\liminf_{n \rightarrow \infty} \inf_{X \in \mathcal{F}} \left( \int_X f_n(x) p_n(dx) - \int_X f(x) p(dx) \right) \geq 0$$

holds if and only if the following two statements hold:

(i) for each  $\epsilon > 0$

$$p(\{x \in \mathbb{X} : f_n(x) \leq f(x) - \epsilon\}) \rightarrow 0 \text{ as } n \rightarrow \infty,$$

and, therefore, there exists a subsequence  $\{f_{n_k}\}_{k=1,2,\dots} \subseteq \{f_n\}_{n=1,2,\dots}$  such that

$$\liminf_{k \rightarrow \infty} f_{n_k}(x) \geq f(x) \quad \text{for } p\text{-a.s. } x \in \mathbb{X};$$

(ii) the following inequality holds:

$$\lim_{K \rightarrow +\infty} \liminf_{n \rightarrow \infty} \int_{\mathbb{X}} f_n(x) \mathbf{I}\{x \in \mathbb{X} : f_n(x) \leq -K\} p_n(dx) \geq 0.$$

# Uniform Lebesgue's Convergence Theorem

*Uniform Lebesgue's Convergence Theorem (F., Kasyanov, and Zgurovsky 2016)*

Let  $(\mathbb{X}, \mathcal{F})$  be a measurable space, a sequence of probability measures  $\{p_n\}_{n=1,2,\dots}$  converge in total variation to a probability measure  $p$  on  $\mathbb{X}$ ,  $f \in L^1(\mathbb{X}; p)$ , and  $f_n \in L^1(\mathbb{X}; p_n)$  for each  $n = 1, 2, \dots$ . Then the equality

$$\lim_{n \rightarrow \infty} \sup_{X \in \mathcal{F}} \left| \int_X f_n(x) p_n(dx) - \int_X f(x) p(dx) \right| = 0$$

holds if and only if the following two statements hold:

- (i) the sequence of functions  $\{f_n\}_{n=1,2,\dots}$  converges in probability  $p$  to  $f$ ; and
- (ii)

$$\lim_{K \rightarrow +\infty} \limsup_{n \rightarrow \infty} \int |f_n(x)| \mathbf{I}\{x \in \mathbb{X} : |f_n(x)| \geq K\} p_n(dx) = 0.$$

# Dunford-Pettis Theorem

## Dunford-Pettis Theorem

Let  $(\mathbb{X}, \mathcal{F})$  be a measurable space,  $p$  be a probability measure on  $\mathbb{X}$ , and  $\{f_n\}_{n=1,2,\dots} \subset L^1(\mathbb{X}; p)$  be a sequence of measurable functions on  $\mathbb{X}$ .

Then the following statements are equivalent:

- (i) there exists  $\{f_{n_k}\}_{k=1,2,\dots} \subset \{f_n\}_{n=1,2,\dots}$  such that  $f_{n_k} \rightarrow f$  weakly in  $L^1(\mathbb{X}; p)$  for some  $f \in L^1(\mathbb{X}; p)$ ;
- (ii) there exists  $\tilde{N} = 1, 2, \dots$  such that  $\{f_{n+\tilde{N}}\}_{n=1,2,\dots}$  is u.i.;
- (iii)  $\{f_n\}_{n=1,2,\dots}$  is a.u.i.

In view of Eberlein-Šmulian theorem, statements (i) and (ii) are equivalent due to the Dunford-Pettis theorem.

# Minorant Condition for a Sequence of Functions

Consider the following condition (depending on how  $p_n$  converges to  $p$ ):

*Minorant condition (when  $p_n \rightarrow p$  weakly)*

Let there exist a sequence of measurable functions  $\{g_n\}$  such that  $g_n \leq f_n$  and

$$-\infty < \int \limsup_{n \rightarrow \infty, y \rightarrow x} g_n(y) p(dx) \leq \liminf_{n \rightarrow \infty} \int g_n(x) p_n(dx).$$

*Minorant condition (when  $p_n \rightarrow p$  setwise)*

Let there exist a sequence of measurable functions  $\{g_n\}$  such that  $g_n \leq f_n$  and

$$-\infty < \int \limsup_{n \rightarrow \infty} g_n(x) p(dx) \leq \liminf_{n \rightarrow \infty} \int g_n(x) p_n(dx).$$

When  $p_n = p$  and  $g_n = g$  for some measurable function  $g$ , the minorant condition in the case when  $p_n \rightarrow p$  setwise becomes the standard condition for classic Fatou's lemma that there exists a measurable function  $g$  such that  $g \leq f_n$  and  $\int g(x) p(dx) > -\infty$ .

# Fatou's Lemma for Varying Probabilities

## Theorem

For probabilities **converging weakly**  $p_n \rightarrow p$  and a sequence of measurable functions  $\{f_n\}$ , if one of the following conditions holds:

- (i) each function  $f_n$  is nonnegative (Serfozo 1981 and F., Kasyanov, Zadoianchuk 2014);
- (ii)  $\{f_n\}$  satisfies the **minorant condition** (F., Kasyanov, Zadoianchuk 2014);
- (iii)  $\{f_n^-\}$  is **a.u.i.** w.r.t.  $\{p_n\}$ ;

then 
$$\liminf_{n \rightarrow \infty} \int f_n(x) p_n(dx) \geq \int \liminf_{y \rightarrow x, n \rightarrow \infty} f_n(y) p(dx).$$

## Theorem

For probabilities **converging setwise**  $p_n \rightarrow p$  and a sequence of measurable functions  $\{f_n\}$ , if one of the following conditions holds:

- (i) each function  $f_n$  is nonnegative (Royden 1963);
- (ii)  $\{f_n\}$  satisfies the **minorant condition** (F., Kasyanov, Zadoianchuk 2014);
- (iii)  $\{f_n^-\}$  is **a.u.i.** w.r.t.  $\{p_n\}$ ;

then 
$$\liminf_{n \rightarrow \infty} \int f_n(x) p_n(dx) \geq \int \liminf_{n \rightarrow \infty} f_n(x) p(dx).$$

# Fatou's Lemma in the Standard Form for Weakly Converging Probabilities

## Lower semi-equicontinuity

A family  $\mathcal{H}$  of real-valued functions on a metric space  $\mathbb{X}$  is called **lower semi-equicontinuous** at the point  $x$  if for each  $\varepsilon > 0$  there exists  $\delta > 0$  such that

$$h(y) > h(x) - \varepsilon \quad \text{for all } y \in B_\delta(x) \text{ and for all } h \in \mathcal{H},$$

where  $B_\delta(x)$  is the open ball of radius  $\delta$  centered at  $x$ .

If the family of functions  $\{f_n\}_{n=1,2,\dots}$  is **lower semi-equicontinuous** at  $x$ , then

$$\liminf_{n \rightarrow \infty, y \rightarrow x} f_n(y) = \liminf_{n \rightarrow \infty} f_n(x),$$

## Equicontinuity

A family  $\mathcal{H}$  of real-valued functions on a metric space  $\mathbb{X}$  is called **equicontinuous** at the point  $x$  if for each  $\varepsilon > 0$  there exists  $\delta > 0$  such that

$$|h(y) - h(x)| < \varepsilon \quad \text{for all } y \in B_\delta(x) \text{ and for all } h \in \mathcal{H},$$

where  $B_\delta(x)$  is the open ball of radius  $\delta$  centered at  $x$ .



# Fatou's Lemma in the Standard Form for Weakly Converging Probabilities

## Theorem

For probabilities *converging weakly*  $p_n \rightarrow p$  and a *lower semi-equicontinuous* family of measurable functions  $\{f_n\}_{n=1,2,\dots}$ , if one of the following conditions holds:

- (i) each function  $f_n$  is nonnegative;
- (ii)  $\{f_n\}$  satisfies the minorant condition;
- (iii)  $\{f_n^-\}$  is a.u.i. w.r.t.  $\{p_n\}$ ;

then

$$\liminf_{n \rightarrow \infty} \int f_n(x) p_n(dx) \geq \int \liminf_{n \rightarrow \infty} f_n(x) p(dx) = \int \liminf_{y \rightarrow x, n \rightarrow \infty} f_n(y) p(dx).$$

# Semi-Convergence in Probability

## Lower semi-convergence in probability

A sequence  $\{f_n\}_{n=1,2,\dots}$  **lower semi-converges in probability  $p$**  to  $f$  if for each  $\varepsilon > 0$

$$p(\{x \in \mathbb{X} : f_n(x) \leq f(x) - \varepsilon\}) \rightarrow 0 \text{ as } n \rightarrow \infty.$$

In particular, for

$$f^*(x) := \liminf_{n \rightarrow \infty} f_n(x), \quad x \in \mathbb{X},$$

$\{f_n\}_{n=1,2,\dots}$  lower semi-converges to  $f^*$  in every probability measure  $p$  on  $\mathbb{X}$ .

If  $\{f_n\}_{n=1,2,\dots}$  **lower semi-converges in probability  $p$**  to some function  $f$ , then there exists a subsequence  $\{f_{n_k}\}_{k=1,2,\dots}$  of the sequence  $\{f_n\}_{n=1,2,\dots}$  such that  $f(x) \leq \liminf_{k \rightarrow \infty} f_{n_k}(x)$  for  $p$ -a.s.  $x \in \mathbb{X}$  (F., Kasyanov, and Zgurovsky 2016).

A sequence  $\{f_n\}_{n=1,2,\dots}$  **upper semi-converges in probability  $p$**  to  $f$  if  $\{-f_n\}_{n=1,2,\dots}$  lower semi-converges in probability  $p$  to  $-f$ .

A sequence  $\{f_n\}_{n=1,2,\dots}$  **converges in probability  $p$**  to  $f$  if and only if  $\{f_n\}_{n=1,2,\dots}$  lower and upper semi-converges in probability  $p$  to  $f$ .

# Fatou's Lemma for Varying Probabilities

## Theorem

For probabilities *converging setwise*  $p_n \rightarrow p$  and measurable functions  $\{f_n\}$  *lower semi-converging in probability*  $p$  to a measurable function  $f$ , if one of the following conditions holds:

- (i) each function  $f_n$  is nonnegative; (ii)  $\{f_n\}$  satisfies the minorant condition;
- (iii)  $\{f_n^-\}$  is a.u.i. w.r.t.  $\{p_n\}$ ;

then

$$\liminf_{n \rightarrow \infty} \int f_n(x) p_n(dx) \geq \int f(x) p(dx).$$

## Theorem

For probabilities *converging weakly*  $p_n \rightarrow p$  and a *lower semi-equicontinuous* family of measurable functions  $\{f_n\}$ , that *lower semi-converges in probability*  $p$  to a measurable function  $f$ , if one of conditions (i), (ii), and (iii) from the theorem above holds, then

$$\liminf_{n \rightarrow \infty} \int f_n(x) p_n(dx) \geq \int f(x) p(dx).$$

In all the cases, we can take  $f(x) := \liminf_{n \rightarrow \infty} f_n(x)$ , but there are examples when

$$f(x) > \liminf_{n \rightarrow \infty} f_n(x) \quad \text{for all } x \in \mathbb{X}.$$

# Lebesgue's Convergence Theorem for Varying Probabilities

## Theorem

For probabilities *converging setwise*  $p_n \rightarrow p$  and measurable functions  $\{f_n\}$  *converging in probability*  $p$  to a measurable function  $f$ , if one of the following conditions holds:

- (i)  $\{f_n\}$  is a.u.i. w.r.t.  $\{p_n\}$ ;
- (ii) both  $\{f_n\}$  and  $\{-f_n\}$  satisfy the minorant condition;

then

$$\lim_{n \rightarrow \infty} \int f_n(x) p_n(dx) = \int f(x) p(dx).$$

# Lebesgue's Convergence Theorem for Varying Probabilities

## Theorem

For probabilities **converging weakly**  $p_n \rightarrow p$  and measurable functions  $\{f_n\}$  such that  $\lim_{n \rightarrow \infty, y \rightarrow x} f_n(y)$  exists for  $p$ -a.s.  $x \in \mathbb{X}$ , if one of the following conditions holds:

- (i)  $\{f_n\}$  is a.u.i. w.r.t.  $\{p_n\}$ ;
- (ii) both  $\{f_n\}$  and  $\{-f_n\}$  satisfy the minorant condition;

then

$$\lim_{n \rightarrow \infty} \int f_n(x) p_n(dx) = \int \lim_{n \rightarrow \infty} f_n(x) p(dx).$$

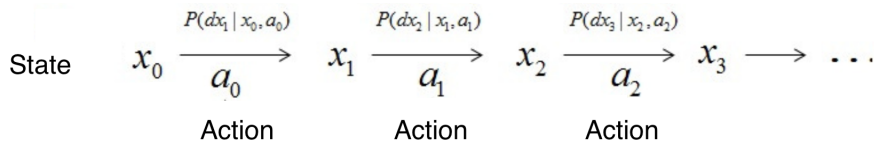
## Theorem

For probabilities **converging weakly**  $p_n \rightarrow p$  and an **equicontinuous** family of functions  $\{f_n\}$ , that **converges in probability**  $p$ , if one of conditions (i) and (ii) from the theorem above holds, then

$$\lim_{n \rightarrow \infty} \int f_n(x) p_n(dx) = \int \lim_{n \rightarrow \infty} f_n(x) p(dx).$$

# Applications: Optimality Inequality and Equations for Average-Cost Markov Decision Processes

## MDP diagram



# Applications: Optimality Inequality and Equations for Average-Cost Markov Decision Processes

Let us consider a Markov decision process (MDP) defined by  $\{\mathbb{X}, \mathbb{A}, P, c\}$ , where

- (i)  $\mathbb{X}$  is a state space;
- (ii)  $\mathbb{A}$  is an action space;
- (iii)  $P(dy|x, a)$  is the transition probability;
- (iv)  $c(x, a)$  is the one-step cost function.

The objective is to minimize

- (i) **finite-horizon costs**:  $v_{N,\alpha}^\pi(x) := \mathbb{E}_x^\pi \left[ \sum_{t=0}^{N-1} \alpha^t c(x_t, a_t) \right]$ , where  $N = 1, 2, \dots$  is the horizon length and  $\alpha \in [0, 1)$  is the discount factor;
- (ii) **infinite-horizon costs**:  $v_\alpha^\pi(x) := \mathbb{E}_x^\pi \left[ \sum_{t=0}^{\infty} \alpha^t c(x_t, a_t) \right]$ ; or
- (iii) **average costs per unit time**:  $w^\pi(x) := \limsup_{N \rightarrow \infty} \frac{1}{N} \mathbb{E}_x^\pi \left[ \sum_{t=0}^{N-1} c(x_t, a_t) \right]$ .

For each function  $V^\pi(x) = v_{N,\alpha}^\pi(x)$ ,  $v_\alpha^\pi(x)$ , or  $w^\pi(x)$ , define the **optimal value**

$$V(x) := \inf_{\pi \in \Pi} V^\pi(x),$$

where  $\Pi$  is the set of all policies.

# Applications: Optimality Inequality and Equations for Average-Cost Markov Decision Processes

Continuity assumptions on transition probabilities and costs:

**Assumption  $\mathbf{W}^*$ :**

1. The transition probability  $P$  is **weakly continuous**.
2. The cost function  $c$  is  **$\mathbb{K}$ -inf-compact** and **bounded below**.

## Definition

A function  $f : \mathbb{X} \times \mathbb{A} \rightarrow \mathbf{R}$  is called  **$\mathbb{K}$ -inf-compact**, if for every compact set  $K \subseteq \mathbb{X}$ , the function  $f : K \times \mathbb{A} \rightarrow \mathbf{R}$  is **inf-compact**.

Suppose Assumption  $\mathbf{W}^*$  holds. Then discounted optimality equation holds (F., Kasyanov, and Zadoianchuk 2012):

$$v_\alpha(x) = \min_a \{c(x, a) + \alpha \int v_\alpha(y)P(dy|x, a)\}.$$

**Vanishing discount factor approach for average-cost MDPs:**

Let  $m_\alpha := \inf_x v_\alpha(x)$  and  $u_\alpha(x) := v_\alpha(x) - m_\alpha$ . Then

$$u_\alpha(x) + (1 - \alpha)m_\alpha = \min_a \left\{ c(x, a) + \alpha \int u_\alpha(y)P(dy|x, a) \right\}.$$



# Optimality Inequality for Average-Cost Markov Decision Processes

The optimality equation for discounted-cost MDP implies

$$(1 - \alpha)m_\alpha + u_\alpha(x) = \min_a \left\{ c(x, a) + \alpha \int u_\alpha(y)P(dy|x, a) \right\}.$$

For a sequence of discount factors  $\{\alpha_n \uparrow 1\}$  and for every sequence  $(x_n, a_n) \rightarrow (x, a)$ , **Fatou's lemma for weakly converging probabilities** implies

$$\liminf_{n \rightarrow \infty} \int u_{\alpha_n}(y)P(dy|x_n, a_n) \geq \int \liminf_{n \rightarrow \infty, y \rightarrow x} u_{\alpha_n}(y)P(dy|x, a).$$

**Assumption B.** The following conditions hold:

- (i)  $w^* := \inf_{x \in \mathbb{X}} w(x) < +\infty$ ;
- (ii)  $\sup_{\alpha < 1} u_\alpha(x) < \infty$  for all  $x \in \mathbb{X}$ .

For  $\alpha \in [0, 1)$  consider  $\underline{w} = \liminf_{\alpha \uparrow 1} (1 - \alpha)m_\alpha$  and  $\bar{w} = \limsup_{\alpha \uparrow 1} (1 - \alpha)m_\alpha$ .

*Theorem (F., Kasyanov, and Zadoianchuk 2012)*

*Suppose Assumptions **W\*** and **B** hold. Consider a sequence  $\{\alpha_n \uparrow 1\}_{n=1,2,\dots}$  of nonnegative discount factors. Then there exist a measurable function*

$$u(x) := \liminf_{n \rightarrow \infty, y \rightarrow x} u_{\alpha_n}(y), \quad x \in \mathbb{X},$$

*and a stationary policy  $\phi$  such that ACOI holds:*

$$\bar{w} + u(x) \geq c(x, \phi(x)) + \int u(y)P(dy|x, \phi(x)), \quad x \in \mathbb{X},$$

*where  $\phi$  is average-cost optimal, and*

$$w(x) = w^\phi(x) = \lim_{\alpha \uparrow 1} (1 - \alpha)v_\alpha(x) = \underline{w} = \bar{w}, \quad x \in \mathbb{X}.$$

# Optimality Equations for Average-Cost Markov Decision Processes

Recall that  $(1 - \alpha)m_\alpha + u_\alpha(x) = \min_a \left\{ c(x, a) + \alpha \int u_\alpha(y)P(dy|x, a) \right\}$ .

For a sequence of discount factors  $\{\alpha_n \uparrow 1\}$  and for every sequence  $(x_n, a_n) \rightarrow (x, a)$ , if **Lebesgue's convergence theorem for weakly converging probabilities** holds:

$$\lim_{n \rightarrow \infty} \int u_{\alpha_n}(y)P(dy|x_n, a_n) = \int \lim_{n \rightarrow \infty} u_{\alpha_n}(y)P(dy|x, a),$$

then average cost optimality equations hold:

$$w + u(x) = c(x, \phi(x)) + \int_{\mathbb{X}} u(y)P(dy|x, \phi(x)) = \min_{a \in \mathbb{A}} [c(x, a) + \int_{\mathbb{X}} u(y)P(dy|x, a)]. \quad (4)$$

## Theorem

**Suppose Assumptions  $W^*$  and  $B$  hold.** Consider a sequence  $\{\alpha_n \uparrow 1\}_{n=1,2,\dots}$  of nonnegative discount factors. If the sequence  $\{u_{\alpha_n}\}_{n=1,2,\dots}$  satisfies:

- (i) the cost function  $c(x, a)$  is continuous in  $x$  for each  $a$ ;
- (ii) the family of functions  $\{u_{\alpha_n}\}_{n=1,2,\dots}$  is **equicontinuous**;
- (iii)  $\{u_{\alpha_n}\}_{n=1,2,\dots}$  is **a.u.i.** w.r.t. any sequence of probabilities defined by  $\{P(\cdot|x_n, a_n)\}$  such that  $(x_n, a_n) \rightarrow (x, a)$ .

then there exist a stationary policy  $\phi$  and a subsequence  $\{\alpha_{n_k}\}_{k=1,2,\dots}$  of  $\{\alpha_n\}_{n=1,2,\dots}$  such that the ACOEs (4) hold with the function  $u(x)$  satisfying

$$u(x) := \lim_{k \rightarrow \infty, y \rightarrow x} u_{\alpha_{n_k}}(y) = \lim_{k \rightarrow \infty} u_{\alpha_{n_k}}(x).$$

# Applications to Inventory Control

We consider an inventory control problem defined by the following parameters:

- (i)  $K > 0$  is a fixed ordering cost;
- (ii)  $\bar{c} > 0$  is the per unit ordering cost;
- (iii)  $\{D_t, t = 1, 2, \dots\}$  is a sequence of i.i.d. nonnegative finite random variables representing the demand at periods  $0, 1, \dots$ ;
- (iv)  $h(x)$  is the holding/backlog cost per period, which is assumed to be a convex real-valued function on  $\mathbf{R}$  with  $h(x) \rightarrow \infty$  as  $|x| \rightarrow \infty$ .

The **dynamics of the system** are defined as

$$x_{t+1} = x_t + a_t - D_{t+1}, \quad t = 0, 1, \dots,$$

where

- (i)  $x_t$  is the amount of inventory at the end of epoch  $t$ ,
- (ii)  $a_t$  is the amount of inventory ordered at the end of epoch  $t$ , where  $a_t \geq 0$ ,
- (iii)  $D_t$  is the demand during the epoch  $t$ ;  $D_t \geq 0$  and  $\{D_t\}$  are i.i.d.

The **one-step costs** are

$$c(x_t, a_t) = K1_{\{a_t \neq 0\}} + \bar{c}a_t + \mathbb{E}h(x_t + a_t - D_{t+1}).$$

**Assumptions  $\mathbf{W}^*$  and  $\mathbf{B}$**  hold for the MDP corresponding to this problem. The cost function  $c(x, a)$  is continuous in  $x$  for each  $a$ .

# Applications to Inventory Control

For a sequence of discount factors  $\{\alpha_n \uparrow 1\}_{n=1,2,\dots}$ , the sequence of functions  $\{u_{\alpha_n}\}_{n=1,2,\dots}$  is **equicontinuous** and **a.u.i.** w.r.t. any sequence of probabilities defined by  $\{P(\cdot|x_n, a_n)\}$  such that  $(x_n, a_n) \rightarrow (x, a)$ .

For the average-cost problem, there exist a sequence of discount factor  $\{\alpha_n\}_{n=1,2,\dots}$  and a stationary policy  $\varphi$  such that ACOEs hold:

$$w + u(x) = K1_{\{\varphi(x) > 0\}} + H(x + \varphi(x)) - \bar{c}x = \min_{a \geq 0} \{\min[K + H(x + a)], H(x)\} - \bar{c}x,$$

where

$$u(x) = \lim_{n \rightarrow \infty, y \rightarrow x} u_{\alpha_n}(y) = \lim_{n \rightarrow \infty} u_{\alpha_n}(x) \quad (5)$$

and

$$H(x) := \bar{c}x + \mathbb{E}h(x - D) + \mathbb{E}u(x - D).$$

## Definition of $K$ -convexity

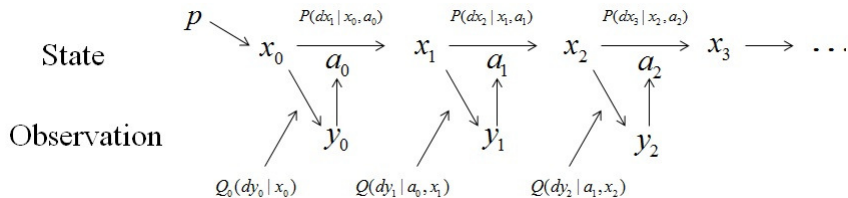
A function  $G : \mathbb{X} \rightarrow \mathbb{R}$  is called  $K$ -convex, where  $K \geq 0$ , if for  $x \leq y$  and for  $\lambda \in (0, 1)$ ,

$$G((1 - \lambda)x + \lambda y) \leq (1 - \lambda)G(x) + \lambda G(y) + \lambda K.$$

Furthermore, the function  $u_{\alpha}$  is  $K$ -convex. Formula (5) implies that the function  $u$  is also  $K$ -convex because **the limit preserves  $K$ -convexity**. This is useful for computing optimal policies.

# Application of the Uniform Fatou Lemma to Partially Observable Markov Decision Process (POMDP)

## POMDP diagram



# Application of the Uniform Fatou Lemma to Partially Observable Markov Decision Process

A *partially observable Markov decision process (POMDP)* is specified by  $(\mathbb{X}, \mathbb{Y}, \mathbb{A}, P, Q, c)$ , where

- (i)  $\mathbb{X}$  is the *state space*,
- (ii)  $\mathbb{Y}$  is the *observation set*,
- (iii)  $\mathbb{A}$  is the *action set*,
- (iv)  $P(dx'|x, a)$  is the *transition probability*,
- (v)  $Q(dy|a, x)$  is the *observation kernel*,
- (vi)  $c : \mathbb{X} \times \mathbb{A} \rightarrow \mathbf{R}$  is the *one-step cost*.

In addition:

- $P_0(dx'|x, a)$  is the *initial state distribution on  $\mathbb{X}$* ,
- $Q_0(dy|a, x)$  is the *distribution of the initial kernel*.

# Reduction of POMDPs to COMDPs

In principle, it is known how to solve a POMDP.

In order to do this, the original states should be replaced by **belief states** which are **probability distributions on the state space  $\mathbb{X}$** .

Let  $\mathbb{P}(E)$  be the set of probability distributions on a set  $E$ . Then a COMDP is an MDP with the state space  $\mathbb{P}(\mathbb{X})$ . For example, if  $\mathbb{X} = \{0, 1\}$ , then  $\mathbb{P}(\mathbb{X}) = [0, 1]$ .

In general, if  $\mathbb{X}$  is a Polish (complete, separable, metric) space then  $\mathbb{P}(\mathbb{X})$  is also a Polish space if the topology of **weak convergence** on  $\mathbb{P}(\mathbb{X})$  is considered. Once an optimal policy for the COMDP is found, it is easy to find an optimal policy for the POMDP.

# Evolution of Posterior Probabilities

Given a **posterior distribution**  $z_t \in \mathbb{P}(\mathbb{X})$  of the state  $x_t \in \mathbb{X}$  and an action  $a_t \in \mathbb{A}$  at time epoch  $t = 0, 1, \dots$ , the joint probability that the state  $x_{t+1} \in B \in \mathcal{B}(\mathbb{X})$  and the observation  $y_{t+1} \in C \in \mathcal{B}(\mathbb{Y})$  is

$$R(B \times C | z_t, a_t) := \int_{\mathbb{X}} \int_B Q(C | a_t, x_{t+1}) P(dx_{t+1} | x_t, a_t) z_t(dx_t)$$

and the probability that the observation  $y_{t+1} \in C \in \mathcal{B}(\mathbb{Y})$  is

$$R'(C | z_t, a_t) = \int_{\mathbb{X}} \int_{\mathbb{X}} Q(C | a_t, x_{t+1}) P(dx_{t+1} | x_t, a_t) z_t(dx_t),$$

where  $\mathcal{B}(\mathbb{X})$  and  $\mathcal{B}(\mathbb{Y})$  are the sets of probabilities on  $\mathbb{X}$  and  $\mathbb{Y}$  respectively.

Then there exist transition probabilities  $H$  from  $\mathbb{P}(\mathbb{X}) \times \mathbb{A} \times \mathbb{Y}$  to  $\mathbb{X}$  such that

$$R(B \times C | z_t, a_t) = \int_C H(B | z_t, a_t, y_{t+1}) R'(dy_{t+1} | z_t, a_t),$$

where  $B \in \mathcal{B}(\mathbb{X})$ ,  $C \in \mathcal{B}(\mathbb{Y})$ ,  $z_t \in \mathbb{P}(\mathbb{X})$  and  $a_t \in \mathbb{A}$ .



# Evolution of Posterior Probabilities

Bayes' formula:

For a posterior distribution  $z_t \in \mathbb{P}(\mathbb{X})$ , action  $a_t \in \mathbb{A}$ , and an observation  $y_{t+1} \in \mathbb{Y}$ , the posterior distribution  $z_{t+1} \in \mathbb{P}(\mathbb{X})$  is

$$z_{t+1} = H(z_t, a_t, y_{t+1}).$$

The observation  $y_{t+1}$  is not available in the COMDP model, and therefore  $y_{t+1}$  is a random variable with the distribution  $R'(\cdot|z_t, a_t)$ , and  $H$  maps  $(z_t, a_t) \in \mathbb{P}(\mathbb{X}) \times \mathbb{A}$  to  $\mathbb{P}(\mathbb{P}(\mathbb{X}))$ . Thus,  $z_{t+1}$  is a random variable with values in  $\mathbb{P}(\mathbb{X})$  whose distribution is defined uniquely by the transition probability

$$q(D|z, a) := \int_{\mathbb{Y}} 1_{\{H(z, a, y) \in D\}} R'(dy|z, a),$$

where  $D \in \mathcal{B}(\mathbb{P}(\mathbb{X}))$ ,  $z \in \mathbb{P}(\mathbb{X})$ ,  $a \in \mathbb{A}$ .

# Existence of Optimal Policies for COMDPs

*Theorem (F., Kasyanov, and Zgurovsky 2016)*

*Suppose the following conditions hold for the POMDP:*

- (i) the cost function  $c$  is  $\mathbb{K}$ -inf-compact;*
- (ii) the transition probability  $P(\cdot|x, a)$  is weakly continuous in  $(x, a)$ ;*
- (iii) the observation probability  $Q(\cdot|a, x)$  is continuous in total variation in  $(a, x)$ .*

*Then, Assumption  $\mathbf{W}^*$  holds for the COMDP. Furthermore, optimal policies exist and convergence of value iteration takes place for discounted cost problems.*

Setwise continuity of  $Q(dy|a, x)$  is not sufficient for the existence of optimal policies. Of course, weak continuity of  $Q$  is not sufficient either (Huizhen (Janey) Yu provided an example in 2012).

The uniform Lebesgue's convergence theorem for uniformly bounded functions was understood to prove this theorem.

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