

Reinforcement Learning Theory

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1 Asymptotic analysis

Consider a function $f : \mathbb{N} \rightarrow \mathbb{R}$.

Definition 1.1. For every $m \in \mathbb{N}$, $\inf_{n \geq m} f(n)$ is the largest $r \in [-\infty, \infty]$ such that $r \leq f(n)$ for every $n \geq m$.

Definition 1.2. For every $m \in \mathbb{N}$, $\sup_{n \geq m} f(n)$ is the smallest $r \in [-\infty, \infty]$ such that $r \geq f(n)$ for every $n \geq m$.

Definition 1.3. The limit inferior $\liminf_{n \rightarrow \infty} f(n)$ is defined by

$$\liminf_{n \rightarrow \infty} f(n) = \lim_{m \rightarrow \infty} \inf_{n \geq m} f(n).$$

Since the function g given by $g(m) = \inf_{n \geq m} f(n)$ is non-decreasing, the limit exists in $[-\infty, \infty]$.

Proposition 1.1. If $z < \liminf_{n \rightarrow \infty} f(n)$, then $z < f(n)$ for all sufficiently large $n \in \mathbb{N}$.

Proposition 1.2. If $z > \liminf_{n \rightarrow \infty} f(n)$, then $z > f(n)$ for infinitely many $n \in \mathbb{N}$.

Definition 1.4. The limit superior $\limsup_{n \rightarrow \infty} f(n)$ is defined by

$$\limsup_{n \rightarrow \infty} f(n) = \lim_{m \rightarrow \infty} \sup_{n \geq m} f(n).$$

Since the function g given by $g(m) = \sup_{n \geq m} f(n)$ is non-increasing, the limit exists in $[-\infty, \infty]$.

Proposition 1.3. If $z > \limsup_{n \rightarrow \infty} f(n)$, then $z > f(n)$ for all sufficiently large $n \in \mathbb{N}$.

Proposition 1.4. If $z < \limsup_{n \rightarrow \infty} f(n)$, then $z < f(n)$ for infinitely many $n \in \mathbb{N}$.

Proposition 1.5. For every $m \in \mathbb{N}$, the infimum, limit inferior, limit superior, and supremum are related by

$$\inf_{n \geq m} f(n) \leq \liminf_{n \rightarrow \infty} f(n) \leq \limsup_{n \rightarrow \infty} f(n) \leq \sup_{n \geq m} f(n).$$

Definition 1.5. The function f is said to converge in $[-\infty, \infty]$ if and only if

$$\liminf_{n \rightarrow \infty} f(n) = \limsup_{n \rightarrow \infty} f(n).$$

Definition 1.6. The set of asymptotically positive function \mathcal{F} is defined by

$$\mathcal{F} = \{f : \mathbb{N} \rightarrow \mathbb{R} \mid \text{there is an } m \in \mathbb{N} \text{ such that } f(n) > 0 \text{ for every } n \geq m\}.$$

Definition 1.7. For every $f \in \mathcal{F}$ and $g \in \mathcal{F}$, let $(f/g) \in \mathcal{F}$ be given by

$$(f/g)(n) = \begin{cases} f(n)/g(n), & \text{if } g(n) \neq 0, \\ 0, & \text{if } g(n) = 0. \end{cases}$$

For convenience, we often write $(f/g)(n)$ as $f(n)/g(n)$, since $(f/g)(n) = f(n)/g(n)$ for all sufficiently large $n \in \mathbb{N}$.

Definition 1.8. If $g \in \mathcal{F}$, then the following subsets of \mathcal{F} are defined:

$$\begin{aligned} o(g) &= \left\{ f \in \mathcal{F} \mid \limsup_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 0 \right\}, \\ O(g) &= \left\{ f \in \mathcal{F} \mid \limsup_{n \rightarrow \infty} \frac{f(n)}{g(n)} < \infty \right\}, \\ \Omega(g) &= \left\{ f \in \mathcal{F} \mid \liminf_{n \rightarrow \infty} \frac{f(n)}{g(n)} > 0 \right\}, \\ \omega(g) &= \left\{ f \in \mathcal{F} \mid \liminf_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \infty \right\}, \\ \Theta(g) &= O(g) \cap \Omega(g). \end{aligned}$$

Consider a real number $a > 0$.

Example 1.1. Since $\lim_{n \rightarrow \infty} an/n^2 = \limsup_{n \rightarrow \infty} an/n^2 = \liminf_{n \rightarrow \infty} an/n^2 = 0$:

- $(n \mapsto an) \in o(n \mapsto n^2)$, often written as $an \in o(n^2)$.
- $(n \mapsto an) \in O(n \mapsto n^2)$, often written as $an \in O(n^2)$.
- $(n \mapsto an) \notin \Omega(n \mapsto n^2)$, often written as $an \notin \Omega(n^2)$.
- $(n \mapsto an) \notin \omega(n \mapsto n^2)$, often written as $an \notin \omega(n^2)$.
- $(n \mapsto an) \notin \Theta(n \mapsto n^2)$, often written as $an \notin \Theta(n^2)$.

Example 1.2. Since $\lim_{n \rightarrow \infty} n^2/an = \limsup_{n \rightarrow \infty} n^2/an = \liminf_{n \rightarrow \infty} n^2/an = \infty$:

- $(n \mapsto n^2) \notin o(n \mapsto an)$, often written as $n^2 \notin o(an)$.
- $(n \mapsto n^2) \notin O(n \mapsto an)$, often written as $n^2 \notin O(an)$.
- $(n \mapsto n^2) \in \Omega(n \mapsto an)$, often written as $n^2 \in \Omega(an)$.
- $(n \mapsto n^2) \in \omega(n \mapsto an)$, often written as $n^2 \in \omega(an)$.
- $(n \mapsto n^2) \notin \Theta(n \mapsto an)$, often written as $n^2 \notin \Theta(an)$.

Example 1.3. Since $\lim_{n \rightarrow \infty} an^2/n^2 = \limsup_{n \rightarrow \infty} an^2/n^2 = \liminf_{n \rightarrow \infty} an^2/n^2 = a$:

- $(n \mapsto an^2) \notin o(n \mapsto n^2)$, often written as $an^2 \notin o(n^2)$.
- $(n \mapsto an^2) \in O(n \mapsto n^2)$, often written as $an^2 \in O(n^2)$.
- $(n \mapsto an^2) \in \Omega(n \mapsto n^2)$, often written as $an^2 \in \Omega(n^2)$.
- $(n \mapsto an^2) \notin \omega(n \mapsto n^2)$, often written as $an^2 \notin \omega(n^2)$.
- $(n \mapsto an^2) \in \Theta(n \mapsto n^2)$, often written as $an^2 \in \Theta(n^2)$.

Proposition 1.6. For every $f \in \mathcal{F}$ and $g \in \mathcal{F}$, unless the product on the right side below is $0 \cdot \infty$ or $\infty \cdot 0$,

$$\limsup_{n \rightarrow \infty} f(n)g(n) \leq \left(\limsup_{n \rightarrow \infty} f(n) \right) \left(\limsup_{n \rightarrow \infty} g(n) \right).$$

Proposition 1.7. For every $f \in \mathcal{F}$ and $g \in \mathcal{F}$, unless the product on the right side below is $0 \cdot \infty$ or $\infty \cdot 0$,

$$\liminf_{n \rightarrow \infty} f(n)g(n) \geq \left(\liminf_{n \rightarrow \infty} f(n) \right) \left(\liminf_{n \rightarrow \infty} g(n) \right).$$

Proposition 1.8. If $f \in \mathcal{F}$ and $\liminf_{n \rightarrow \infty} f(n) > 0$, then

$$\limsup_{n \rightarrow \infty} \frac{1}{f(n)} = \frac{1}{\liminf_{n \rightarrow \infty} f(n)},$$

where $1/\infty$ is used to denote 0 on the right side above.

Proof. If $\liminf_{n \rightarrow \infty} f(n) = \infty$, then $\lim_{n \rightarrow \infty} f(n) = \infty$ and $\limsup_{n \rightarrow \infty} 1/f(n) = \lim_{n \rightarrow \infty} 1/f(n) = 0$.

If $\liminf_{n \rightarrow \infty} f(n) < \infty$, consider the function g given by $g(m) = \inf_{n \geq m} f(n) < \infty$, which is non-decreasing. Because $\lim_{m \rightarrow \infty} g(m) = \liminf_{n \rightarrow \infty} f(n) > 0$, there is an $N \in \mathbb{N}$ such that $g(m) > 0$ for every $m \geq N$, which also implies $f(n) > 0$ for every $n \geq N$. For every $m \in \mathbb{N}$, since the smaller the denominator the larger the fraction,

$$\sup_{n \geq \max(N, m)} \frac{1}{f(n)} = \frac{1}{\inf_{n \geq \max(N, m)} f(n)}.$$

By taking the limit when $m \rightarrow \infty$, since both sides are non-increasing with respect to m ,

$$\limsup_{n \rightarrow \infty} \frac{1}{f(n)} = \lim_{m \rightarrow \infty} \sup_{n \geq \max(N, m)} \frac{1}{f(n)} = \lim_{m \rightarrow \infty} \frac{1}{\inf_{n \geq \max(N, m)} f(n)} = \frac{1}{\liminf_{n \rightarrow \infty} f(n)}.$$

□

Proposition 1.9. If $f \in \mathcal{F}$ and $\limsup_{n \rightarrow \infty} f(n) < \infty$, then

$$\liminf_{n \rightarrow \infty} \frac{1}{f(n)} = \frac{1}{\limsup_{n \rightarrow \infty} f(n)},$$

where $1/0$ is used to denote ∞ on the right side above.

Proof. If $\limsup_{n \rightarrow \infty} f(n) = 0$, then $\lim_{n \rightarrow \infty} f(n) = 0$ and $\liminf_{n \rightarrow \infty} 1/f(n) = \lim_{n \rightarrow \infty} 1/f(n) = \infty$.

If $\limsup_{n \rightarrow \infty} f(n) > 0$, consider the function g given by $g(m) = \sup_{n \geq m} f(n) > 0$, which is non-increasing. Because $\lim_{m \rightarrow \infty} g(m) = \limsup_{n \rightarrow \infty} f(n) < \infty$, there is an $N \in \mathbb{N}$ such that $g(m) < \infty$ for every $m \geq N$. For every $m \in \mathbb{N}$, since the larger the denominator the smaller the fraction,

$$\inf_{n \geq \max(N, m)} \frac{1}{f(n)} = \frac{1}{\sup_{n \geq \max(N, m)} f(n)}.$$

By taking the limit when $m \rightarrow \infty$, since both sides are non-decreasing with respect to m ,

$$\liminf_{n \rightarrow \infty} \frac{1}{f(n)} = \lim_{m \rightarrow \infty} \inf_{n \geq \max(N, m)} \frac{1}{f(n)} = \lim_{m \rightarrow \infty} \frac{1}{\sup_{n \geq \max(N, m)} f(n)} = \frac{1}{\limsup_{n \rightarrow \infty} f(n)}.$$

□

Consider the functions $f \in \mathcal{F}$, $g \in \mathcal{F}$, and $h \in \mathcal{F}$.

Proposition 1.10. If $f \in \mathcal{F}$, then $f \in O(f)$, $f \in \Omega(f)$, and $f \in \Theta(f)$. Furthermore, $o(f) \subseteq O(f)$ and $\omega(f) \subseteq \Omega(f)$.

Proposition 1.11. If $f \in o(g)$ and $g \in o(h)$, then $f \in o(h)$.

Proof. By Proposition 1.6,

$$0 \leq \limsup_{n \rightarrow \infty} \frac{f(n)}{h(n)} = \limsup_{n \rightarrow \infty} \frac{f(n)g(n)}{g(n)h(n)} \leq \left(\limsup_{n \rightarrow \infty} \frac{f(n)}{g(n)} \right) \left(\limsup_{n \rightarrow \infty} \frac{g(n)}{h(n)} \right) = 0.$$

□

Proposition 1.12. If $f \in O(g)$ and $g \in O(h)$, then $f \in O(h)$.

Proof. By Proposition 1.6,

$$\limsup_{n \rightarrow \infty} \frac{f(n)}{h(n)} = \limsup_{n \rightarrow \infty} \frac{f(n)g(n)}{g(n)h(n)} \leq \left(\limsup_{n \rightarrow \infty} \frac{f(n)}{g(n)} \right) \left(\limsup_{n \rightarrow \infty} \frac{g(n)}{h(n)} \right) < \infty.$$

□

Proposition 1.13. If $f \in \Omega(g)$ and $g \in \Omega(h)$, then $f \in \Omega(h)$.

Proof. By Proposition 1.7,

$$\liminf_{n \rightarrow \infty} \frac{f(n)}{h(n)} = \liminf_{n \rightarrow \infty} \frac{f(n)g(n)}{g(n)h(n)} \geq \left(\liminf_{n \rightarrow \infty} \frac{f(n)}{g(n)} \right) \left(\liminf_{n \rightarrow \infty} \frac{g(n)}{h(n)} \right) > 0.$$

□

Proposition 1.14. If $f \in \omega(g)$ and $g \in \omega(h)$, then $f \in \omega(h)$.

Proof. By Proposition 1.7,

$$\infty \geq \liminf_{n \rightarrow \infty} \frac{f(n)}{h(n)} = \liminf_{n \rightarrow \infty} \frac{f(n)g(n)}{g(n)h(n)} \geq \left(\liminf_{n \rightarrow \infty} \frac{f(n)}{g(n)} \right) \left(\liminf_{n \rightarrow \infty} \frac{g(n)}{h(n)} \right) = \infty.$$

□

Proposition 1.15. If $f \in \Theta(g)$ and $g \in \Theta(h)$, then $f \in \Theta(h)$.

Proof. Since $f \in O(g)$ and $g \in O(h)$, we have $f \in O(h)$. Since $f \in \Omega(g)$ and $g \in \Omega(h)$, we have $f \in \Omega(h)$. □

Theorem 1.1. If $f \in \mathcal{F}$ and $g \in \mathcal{F}$, then

- $f \in O(g)$ if and only if $g \in \Omega(f)$.
- $f \in o(g)$ if and only if $g \in \omega(f)$.

Proof. If $f \in O(g)$ and $f \notin o(g)$, then $\limsup_{n \rightarrow \infty} f(n)/g(n) \in (0, \infty)$. In that case, $g \in \Omega(f)$, since

$$\liminf_{n \rightarrow \infty} \frac{g(n)}{f(n)} = \frac{1}{\limsup_{n \rightarrow \infty} f(n)/g(n)} > 0.$$

If $f \in O(g)$ and $f \in o(g)$, then $\limsup_{n \rightarrow \infty} f(n)/g(n) = 0$ and $\liminf_{n \rightarrow \infty} g(n)/f(n) = \infty$, so that $g \in \omega(f)$.

If $g \in \Omega(f)$ and $g \notin \omega(f)$, then $\liminf_{n \rightarrow \infty} g(n)/f(n) \in (0, \infty)$. In that case, $f \in O(g)$, since

$$\limsup_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \frac{1}{\liminf_{n \rightarrow \infty} g(n)/f(n)} < \infty.$$

If $g \in \Omega(f)$ and $g \in \omega(f)$, then $\liminf_{n \rightarrow \infty} g(n)/f(n) = \infty$ and $\limsup_{n \rightarrow \infty} f(n)/g(n) = 0$, so that $f \in o(g)$. \square

Proposition 1.16. If $f \in \mathcal{F}$ and $g \in \mathcal{F}$, then $f \in \Theta(g)$ if and only if $g \in \Theta(f)$.

Proof. If $f \in \Theta(g)$, then $f \in O(g)$ implies $g \in \Omega(f)$ and $f \in \Omega(g)$ implies $g \in O(f)$; and vice versa. \square

Definition 1.9. The following binary relations are defined on the set \mathcal{F} :

- $f \prec g$ if and only if $f \in o(g)$.
- $f \lesssim g$ if and only if $f \in O(g)$.
- $f \gtrsim g$ if and only if $f \in \Omega(g)$.
- $f \succ g$ if and only if $f \in \omega(g)$.
- $f \sim g$ if and only if $f \in \Theta(g)$.

Proposition 1.17. The binary relations \prec and \succ are strict preorders.

Proof. By the definition of strict preorder:

- It is false that $f \prec f$. If $f \prec g$ and $g \prec h$, then $f \prec h$.
- It is false that $f \succ g$. If $f \succ g$ and $g \succ h$, then $f \succ h$.

\square

Proposition 1.18. The binary relations \lesssim and \gtrsim are preorders.

Proof. By the definition of preorder:

- It is true that $f \lesssim f$. If $f \lesssim g$ and $g \lesssim h$, then $f \lesssim h$.
- It is true that $f \gtrsim f$. If $f \gtrsim g$ and $g \gtrsim h$, then $f \gtrsim h$.

\square

Proposition 1.19. The binary relation \sim is an equivalence relation.

Proof. It is true that $f \sim f$. If $f \sim g$, then $g \sim f$; if $g \sim f$, then $f \sim g$. If $f \sim g$ and $g \sim h$, then $f \sim h$. \square

Proposition 1.20. The binary relations defined on the set \mathcal{F} are related by the following:

1. If $f \prec g$, then $f \lesssim g$.
2. If $f \succ g$, then $f \gtrsim g$.
3. If $f \lesssim g$ and $g \lesssim f$, then $f \sim g$.
4. If $f \gtrsim g$ and $g \gtrsim f$, then $f \sim g$.

5. If $f \prec g$, then not $f \succsim g$.

6. If $f \succ g$, then not $f \lesssim g$.

Proof. The first two claims follow from Proposition 1.10; the next two follow from Theorem 1.1; and the last two follow from the fact that $\liminf_{n \rightarrow \infty} f(n)/g(n) \leq \limsup_{n \rightarrow \infty} f(n)/g(n)$. \square

Definition 1.10. Let $A \in \{o, O, \Omega, \omega, \Theta\}$. For any functions $f : \mathbb{N} \rightarrow \mathbb{R}$, $g : \mathbb{N} \rightarrow \mathbb{R}$, and $h \in \mathcal{F}$,

$$f(n) = g(n) + A(h(n))$$

denotes that there is a function $l \in A(h)$ such that $f = g + l$.

Consider a function $f \in \mathcal{F}$.

Example 1.4. If $a > 0$, then $f(n) = \Theta(af(n))$. In order to see this, note that $f = 0 + f$ and $f \in \Theta(af)$, since

$$0 < \liminf_{n \rightarrow \infty} \frac{f(n)}{af(n)} = \limsup_{n \rightarrow \infty} \frac{f(n)}{af(n)} = \frac{1}{a} < \infty.$$

Example 1.5. If $f(n) = n^2 + O(n^2)$, then $f(n) = \Theta(n^2)$. Suppose that there is an $l \in O(n \mapsto n^2)$ such that $f(n) = n^2 + l(n)$ for every $n \in \mathbb{N}$. In that case,

$$\begin{aligned} \limsup_{n \rightarrow \infty} \frac{f(n)}{n^2} &= \limsup_{n \rightarrow \infty} \frac{n^2 + l(n)}{n^2} = 1 + \limsup_{n \rightarrow \infty} \frac{l(n)}{n^2} < \infty, \\ \liminf_{n \rightarrow \infty} \frac{f(n)}{n^2} &= \liminf_{n \rightarrow \infty} \frac{n^2 + l(n)}{n^2} = 1 + \liminf_{n \rightarrow \infty} \frac{l(n)}{n^2} > 0, \end{aligned}$$

so that $f \in \Theta(n \mapsto n^2)$. Since $f = 0 + f$ and $f \in \Theta(n \mapsto n^2)$, we have $f(n) = \Theta(n^2)$.

2 Subgaussian random variables

For details about the notation employed below, see the measure-theoretic probability notes by the same author.

Consider a probability triple $(\Omega, \mathcal{F}, \mathbb{P})$ and a constant $\sigma > 0$.

Definition 2.1. A random variable $X : \Omega \rightarrow \mathbb{R}$ is 0-subgaussian if and only if $\mathbb{P}(X = 0) = 1$.

Definition 2.2. A random variable $X : \Omega \rightarrow \mathbb{R}$ is σ -subgaussian if and only if, for every $\lambda \in \mathbb{R}$,

$$\mathbb{E}(e^{\lambda X}) \leq e^{\frac{\lambda^2 \sigma^2}{2}}.$$

Proposition 2.1. If a random variable $X : \Omega \rightarrow \mathbb{R}$ is σ -subgaussian, then, for every $\lambda \in \mathbb{R}$,

$$\mathbb{E}(e^{\lambda|X|}) \leq 2e^{\frac{\lambda^2 \sigma^2}{2}}.$$

Proof. For every $\lambda \in \mathbb{R}$, note that $e^{\lambda|X|} = e^{\lambda X} \mathbb{I}_{\{X \geq 0\}} + e^{-\lambda X} \mathbb{I}_{\{X < 0\}}$. Since $e^x > 0$ for every $x \in \mathbb{R}$, note that $\mathbb{E}(e^{\lambda X} \mathbb{I}_{\{X \geq 0\}}) \leq \mathbb{E}(e^{\lambda X}) \leq e^{\frac{\lambda^2 \sigma^2}{2}}$ and $\mathbb{E}(e^{-\lambda X} \mathbb{I}_{\{X < 0\}}) \leq \mathbb{E}(e^{-\lambda X}) \leq e^{\frac{(-\lambda)^2 \sigma^2}{2}} = e^{\frac{\lambda^2 \sigma^2}{2}}$. Therefore,

$$\mathbb{E}(e^{\lambda|X|}) = \mathbb{E}(e^{\lambda X} \mathbb{I}_{\{X \geq 0\}}) + \mathbb{E}(e^{-\lambda X} \mathbb{I}_{\{X < 0\}}) \leq 2e^{\frac{\lambda^2 \sigma^2}{2}}.$$

□

Proposition 2.2. If a random variable $X : \Omega \rightarrow \mathbb{R}$ is σ -subgaussian, then $\mathbb{E}(X) = 0$.

Proof. Recall that $e^x \geq x + 1$ for every $x \in \mathbb{R}$. Therefore, $\mathbb{E}(e^{|X|}) \geq \mathbb{E}(|X|) + 1$ and $\mathbb{E}(|X|) \leq 2e^{\frac{\sigma^2}{2}} - 1$.

For every $\lambda \in \mathbb{R}$, recall that the function $\phi : \mathbb{R} \rightarrow \mathbb{R}$ given by $\phi(x) = e^{\lambda x}$ is convex. By Jensen's inequality,

$$e^{\lambda \mathbb{E}(X)} = \phi(\mathbb{E}(X)) \leq \mathbb{E}(\phi(X)) = \mathbb{E}(e^{\lambda X}) \leq e^{\frac{\lambda^2 \sigma^2}{2}},$$

so that $\lambda \mathbb{E}(X) \leq \lambda^2 \sigma^2 / 2$ for every $\lambda \in \mathbb{R}$. If $\lambda < 0$, then $\mathbb{E}(X) \geq \lambda \sigma^2 / 2$. If $\lambda > 0$, then $\mathbb{E}(X) \leq \lambda \sigma^2 / 2$. Therefore,

$$0 = \lim_{\lambda \rightarrow 0^-} \frac{\lambda \sigma^2}{2} \leq \mathbb{E}(X) \leq \lim_{\lambda \rightarrow 0^+} \frac{\lambda \sigma^2}{2} = 0.$$

□

Proposition 2.3. If a random variable $X : \Omega \rightarrow \mathbb{R}$ is σ -subgaussian, then $\text{Var}(X) \leq \sigma^2$.

Proof. Recall that $e^x = \sum_{n=0}^{\infty} x^n / n!$ for every $x \in \mathbb{R}$. Therefore, for every $\lambda \geq 0$ and $k \in \mathbb{N}$,

$$e^{\lambda|X|} = \sum_{n=0}^{\infty} \frac{\lambda^n |X|^n}{n!} \geq \sum_{n=0}^k \frac{\lambda^n |X|^n}{n!} = \sum_{n=0}^k \left| \frac{\lambda^n X^n}{n!} \right| \geq \left| \sum_{n=0}^k \frac{\lambda^n X^n}{n!} \right|.$$

Since $\mathbb{E}(e^{\lambda|X|}) < \infty$, note that $\mathbb{E}(|X|^k) < \infty$ for every $k \in \mathbb{N}$. By the dominated convergence theorem,

$$\mathbb{E}(e^{\lambda X}) = \mathbb{E}\left(\sum_{n=0}^{\infty} \frac{\lambda^n X^n}{n!}\right) = \sum_{n=0}^{\infty} \frac{\lambda^n \mathbb{E}(X^n)}{n!} = 1 + \frac{\lambda^2 \mathbb{E}(X^2)}{2} + \sum_{n=3}^{\infty} \frac{\lambda^n \mathbb{E}(X^n)}{n!},$$

where we also used the fact that $\mathbb{E}(X) = 0$.

For every $\lambda \in [0, 1]$, note that $\lambda^{2n} \leq \lambda^4$ for every $n \geq 2$. Therefore, for every $\lambda \in [0, 1]$,

$$e^{\frac{\lambda^2 \sigma^2}{2}} = \sum_{n=0}^{\infty} \frac{\lambda^{2n} \sigma^{2n}}{2^n n!} = 1 + \frac{\lambda^2 \sigma^2}{2} + \sum_{n=2}^{\infty} \frac{\lambda^{2n} \sigma^{2n}}{2^n n!} \leq 1 + \frac{\lambda^2 \sigma^2}{2} + \lambda^4 \sum_{n=2}^{\infty} \frac{\sigma^{2n}}{2^n n!} \leq 1 + \frac{\lambda^2 \sigma^2}{2} + \lambda^4 e^{\frac{\sigma^2}{2}}.$$

For every $\lambda \in [0, 1]$, by the definition of a σ -subgaussian random variable,

$$\frac{\lambda^2 \mathbb{E}(X^2)}{2} + \sum_{n=3}^{\infty} \frac{\lambda^n \mathbb{E}(X^n)}{n!} \leq \frac{\lambda^2 \sigma^2}{2} + \lambda^4 e^{\frac{\sigma^2}{2}}.$$

For every $\lambda \in (0, 1]$, by multiplying both sides by $2/\lambda^2$,

$$\mathbb{E}(X^2) + 2 \sum_{n=3}^{\infty} \frac{\lambda^{n-2} \mathbb{E}(X^n)}{n!} \leq \sigma^2 + 2\lambda^2 e^{\frac{\sigma^2}{2}}.$$

By taking the limit of both sides when $\lambda \rightarrow 0^+$,

$$\mathbb{E}(X^2) + 2 \lim_{\lambda \rightarrow 0^+} \sum_{n=3}^{\infty} \frac{\lambda^{n-2} \mathbb{E}(X^n)}{n!} \leq \sigma^2 + 2e^{\frac{\sigma^2}{2}} \lim_{\lambda \rightarrow 0^+} \lambda^2 = \sigma^2.$$

If the limit on the left side above is zero, then $\mathbb{E}(X^2) \leq \sigma^2$. In that case, considering that $\mathbb{E}(X) = 0$, note that $\text{Var}(X) = \mathbb{E}(X^2) - \mathbb{E}(X)^2 = \mathbb{E}(X^2) \leq \sigma^2$, so that the proof will be complete. For every $\lambda \in (0, 1]$,

$$\left| \sum_{n=3}^{\infty} \frac{\lambda^{n-2} \mathbb{E}(X^n)}{n!} \right| = \lambda \left| \sum_{n=3}^{\infty} \frac{\lambda^{n-3} \mathbb{E}(X^n)}{n!} \right| \leq \lambda \sum_{n=3}^{\infty} \frac{\lambda^{n-3} |\mathbb{E}(X^n)|}{n!}.$$

For every $k \in \mathbb{N}$ and $\lambda \in (0, 1]$, note that $\mathbb{E}(X^k) \leq \mathbb{E}(|X|^k) < \infty$ and $\lambda^k \leq 1$. Therefore,

$$\left| \sum_{n=3}^{\infty} \frac{\lambda^{n-2} \mathbb{E}(X^n)}{n!} \right| \leq \lambda \sum_{n=3}^{\infty} \frac{\lambda^{n-3} \mathbb{E}(|X|^n)}{n!} \leq \lambda \sum_{n=3}^{\infty} \frac{\mathbb{E}(|X|^n)}{n!} \leq \lambda \mathbb{E}(e^{|X|}) \leq 2\lambda e^{\frac{\sigma^2}{2}},$$

so that

$$0 \leq \lim_{\lambda \rightarrow 0^+} \left| \sum_{n=3}^{\infty} \frac{\lambda^{n-2} \mathbb{E}(X^n)}{n!} \right| \leq 2e^{\frac{\sigma^2}{2}} \lim_{\lambda \rightarrow 0^+} \lambda = 0.$$

□

Proposition 2.4. If a random variable $X : \Omega \rightarrow \mathbb{R}$ is σ -subgaussian, then cX is $|c|\sigma$ -subgaussian for every $c \in \mathbb{R}$.

Proof. This proposition is trivial if $c = 0$. If $c \neq 0$, cX is a random variable and, for every $\lambda \in \mathbb{R}$,

$$\mathbb{E}(e^{\lambda(cX)}) = \mathbb{E}(e^{(\lambda c)X}) \leq e^{\frac{(\lambda c)^2 \sigma^2}{2}} = e^{\frac{\lambda^2 c^2 \sigma^2}{2}} = e^{\frac{\lambda^2 |c|^2 \sigma^2}{2}} = e^{\frac{\lambda^2 (|c|\sigma)^2}{2}}.$$

□

Consider the constants $\sigma_1 > 0$ and $\sigma_2 > 0$.

Proposition 2.5. If the random variable $X_1 : \Omega \rightarrow \mathbb{R}$ is σ_1 -subgaussian, the random variable X_2 is σ_2 -subgaussian, and X_1 and X_2 are independent, then $X_1 + X_2$ is $\sqrt{\sigma_1^2 + \sigma_2^2}$ -subgaussian.

Proof. For every $\lambda \in \mathbb{R}$, because $e^{\lambda X_1}$ and $e^{\lambda X_2}$ are independent and \mathbb{P} -integrable,

$$\mathbb{E}(e^{\lambda(X_1+X_2)}) = \mathbb{E}(e^{\lambda X_1 + \lambda X_2}) = \mathbb{E}(e^{\lambda X_1} e^{\lambda X_2}) = \mathbb{E}(e^{\lambda X_1}) \mathbb{E}(e^{\lambda X_2}) \leq e^{\frac{\lambda^2 \sigma_1^2}{2}} e^{\frac{\lambda^2 \sigma_2^2}{2}} = e^{\frac{\lambda^2 (\sigma_1^2 + \sigma_2^2)}{2}},$$

so that the random variable $X_1 + X_2$ is $\sqrt{\sigma_1^2 + \sigma_2^2}$ -subgaussian. □

Proposition 2.6. If the random variable $X_1 : \Omega \rightarrow \mathbb{R}$ is σ_1 -subgaussian and the random variable X_2 is σ_2 -subgaussian, then $X_1 + X_2$ is $(\sigma_1 + \sigma_2)$ -subgaussian.

Proof. Note that $\mathbb{E}(|e^{\lambda X_1}|^p) = \mathbb{E}(e^{\lambda p X_1}) < \infty$ and $\mathbb{E}(|e^{\lambda X_2}|^q) = \mathbb{E}(e^{\lambda q X_2}) < \infty$ for every $\lambda \in \mathbb{R}$, $p \geq 1$, and $q \geq 1$. By Hölder's inequality, if $p > 1$ and $p^{-1} + q^{-1} = 1$, then

$$\mathbb{E}(e^{\lambda(X_1+X_2)}) = \mathbb{E}(e^{\lambda X_1 + \lambda X_2}) = \mathbb{E}(e^{\lambda X_1} e^{\lambda X_2}) \leq \mathbb{E}(|e^{\lambda X_1}|^p)^{\frac{1}{p}} \mathbb{E}(|e^{\lambda X_2}|^q)^{\frac{1}{q}} = \mathbb{E}(e^{\lambda p X_1})^{\frac{1}{p}} \mathbb{E}(e^{\lambda q X_2})^{\frac{1}{q}}.$$

By the definition of subgaussian random variables,

$$\mathbb{E}(e^{\lambda(X_1+X_2)}) \leq \left(e^{\frac{\lambda^2 p^2 \sigma_1^2}{2}} \right)^{\frac{1}{p}} \left(e^{\frac{\lambda^2 q^2 \sigma_2^2}{2}} \right)^{\frac{1}{q}} = e^{\frac{\lambda^2 p \sigma_1^2}{2}} e^{\frac{\lambda^2 q \sigma_2^2}{2}} = e^{\frac{\lambda^2}{2} (p \sigma_1^2 + q \sigma_2^2)}.$$

Let $p = (\sigma_1 + \sigma_2)/\sigma_1$ and $q = (\sigma_1 + \sigma_2)/\sigma_2$, so that $p > 1$ and $p^{-1} + q^{-1} = 1$. In that case, for every $\lambda \in \mathbb{R}$,

$$\mathbb{E}(e^{\lambda(X_1+X_2)}) \leq e^{\frac{\lambda^2}{2} \left(\frac{\sigma_1 + \sigma_2}{\sigma_1} \sigma_1^2 + \frac{\sigma_1 + \sigma_2}{\sigma_2} \sigma_2^2 \right)} = e^{\frac{\lambda^2}{2} (\sigma_1^2 + 2\sigma_1 \sigma_2 + \sigma_2^2)} = e^{\frac{\lambda^2 (\sigma_1 + \sigma_2)^2}{2}},$$

so that the random variable $X_1 + X_2$ is $(\sigma_1 + \sigma_2)$ -subgaussian. □

Proposition 2.7. If a random variable $X : \Omega \rightarrow \mathbb{R}$ has a normal distribution with mean 0 and variance 1, then X is 1-subgaussian.

Proof. For every $\lambda \in \mathbb{R}$, considering a probability density function for the random variable X ,

$$\mathbb{E}(e^{\lambda X}) = \int_{\mathbb{R}} e^{\lambda x} \frac{e^{-\frac{x^2}{2}}}{\sqrt{2\pi}} \text{Leb}(dx) = \int_{\mathbb{R}} \frac{e^{\lambda x - \frac{x^2}{2}}}{\sqrt{2\pi}} \text{Leb}(dx) = e^{\frac{\lambda^2}{2}} \int_{\mathbb{R}} \frac{e^{-\frac{(x-\lambda)^2}{2}}}{\sqrt{2\pi}} \text{Leb}(dx) = e^{\frac{\lambda^2}{2}}.$$

where we used the fact that $\lambda x - \frac{x^2}{2} = -\frac{(x-\lambda)^2}{2} + \frac{\lambda^2}{2}$ and recognized a probability density function for a random variable that has a normal distribution with mean λ and variance 1. \square

Proposition 2.8. If a random variable $X : \Omega \rightarrow \mathbb{R}$ has a normal distribution with mean 0 and variance σ^2 , then X is σ -subgaussian.

Proof. Recall that X/σ has a normal distribution with mean 0 and variance $\sigma^2/\sigma^2 = 1$. Therefore, X/σ is 1-subgaussian, so that $\sigma \frac{X}{\sigma} = X$ is $|\sigma|$ -subgaussian. \square

Lemma 2.1 (Hoeffding's lemma). If $X : \Omega \rightarrow \mathbb{R}$ is a random variable such that $\mathbb{E}(X) = 0$ and $\mathbb{P}(X \in [a, b]) = 1$ for some $a < b$, then X is $(b - a)/2$ -subgaussian.

3 Concentration of measure

Consider a probability triple $(\Omega, \mathcal{F}, \mathbb{P})$ and a constant $\sigma > 0$.

Theorem 3.1. If $X : \Omega \rightarrow \mathbb{R}$ is a σ -subgaussian random variable, then, for every $\epsilon \geq 0$,

$$\begin{aligned}\mathbb{P}(X \leq -\epsilon) &\leq e^{-\frac{\epsilon^2}{2\sigma^2}}, \\ \mathbb{P}(X \geq \epsilon) &\leq e^{-\frac{\epsilon^2}{2\sigma^2}}, \\ \mathbb{P}(|X| \geq \epsilon) &\leq 2e^{-\frac{\epsilon^2}{2\sigma^2}}.\end{aligned}$$

Proof. Recall that the function $g : \mathbb{R} \rightarrow [0, \infty]$ given by $g(x) = e^{\lambda x}$ is non-decreasing for every $\lambda \geq 0$. For every $\epsilon \in \mathbb{R}$, by Markov's inequality,

$$\begin{aligned}\mathbb{E}(e^{-\lambda X}) &= \mathbb{E}(g(-X)) \geq g(\epsilon)\mathbb{P}(-X \geq \epsilon) = e^{\lambda\epsilon}\mathbb{P}(X \leq -\epsilon), \\ \mathbb{E}(e^{\lambda X}) &= \mathbb{E}(g(X)) \geq g(\epsilon)\mathbb{P}(X \geq \epsilon) = e^{\lambda\epsilon}\mathbb{P}(X \geq \epsilon).\end{aligned}$$

For every $\epsilon \in \mathbb{R}$ and $\lambda \geq 0$, since X is a σ -subgaussian random variable and $e^{\lambda\epsilon} > 0$,

$$\begin{aligned}\mathbb{P}(X \leq -\epsilon) &\leq \frac{\mathbb{E}(e^{-\lambda X})}{e^{\lambda\epsilon}} \leq \frac{e^{\frac{(-\lambda)^2\sigma^2}{2}}}{e^{\lambda\epsilon}} = e^{\frac{\lambda^2\sigma^2}{2} - \lambda\epsilon}, \\ \mathbb{P}(X \geq \epsilon) &\leq \frac{\mathbb{E}(e^{\lambda X})}{e^{\lambda\epsilon}} \leq \frac{e^{\frac{\lambda^2\sigma^2}{2}}}{e^{\lambda\epsilon}} = e^{\frac{\lambda^2\sigma^2}{2} - \lambda\epsilon}.\end{aligned}$$

For every $\epsilon \geq 0$, let $\lambda = \epsilon/\sigma^2$, so that $\lambda \geq 0$. In that case,

$$\begin{aligned}\mathbb{P}(X \leq -\epsilon) &\leq e^{\frac{\epsilon^2}{\sigma^4} \frac{\sigma^2}{2} - \frac{\epsilon^2}{\sigma^2}} = e^{\frac{\epsilon^2}{2\sigma^2} - \frac{\epsilon^2}{\sigma^2}} = e^{\frac{\epsilon^2}{\sigma^2}(\frac{1}{2} - 1)} = e^{-\frac{\epsilon^2}{2\sigma^2}}, \\ \mathbb{P}(X \geq \epsilon) &\leq e^{\frac{\epsilon^2}{\sigma^4} \frac{\sigma^2}{2} - \frac{\epsilon^2}{\sigma^2}} = e^{\frac{\epsilon^2}{2\sigma^2} - \frac{\epsilon^2}{\sigma^2}} = e^{\frac{\epsilon^2}{\sigma^2}(\frac{1}{2} - 1)} = e^{-\frac{\epsilon^2}{2\sigma^2}}.\end{aligned}$$

Therefore, for every $\epsilon \geq 0$,

$$\mathbb{P}(|X| \geq \epsilon) = \mathbb{P}(\{X \leq -\epsilon\} \cup \{X \geq \epsilon\}) \leq \mathbb{P}(X \leq -\epsilon) + \mathbb{P}(X \geq \epsilon) \leq 2e^{-\frac{\epsilon^2}{2\sigma^2}}.$$

□

Proposition 3.1. If $X : \Omega \rightarrow \mathbb{R}$ is a σ -subgaussian random variable, then, for every $\delta \in (0, 1]$,

$$\begin{aligned}\mathbb{P}\left(X \leq -\sqrt{2\sigma^2 \log(1/\delta)}\right) &\leq \delta, \\ \mathbb{P}\left(X \geq \sqrt{2\sigma^2 \log(1/\delta)}\right) &\leq \delta, \\ \mathbb{P}\left(|X| \geq \sqrt{2\sigma^2 \log(2/\delta)}\right) &\leq \delta.\end{aligned}$$

Proof. Let $\delta \in (0, 1]$. If $\epsilon = \sqrt{2\sigma^2 \log(1/\delta)}$, then $\epsilon \geq 0$ and $\delta = e^{-\frac{\epsilon^2}{2\sigma^2}}$, which implies the first two inequalities. If $\epsilon = \sqrt{2\sigma^2 \log(2/\delta)}$, then $\epsilon \geq 0$ and $\delta = 2e^{-\frac{\epsilon^2}{2\sigma^2}}$, which implies the last inequality. □

Proposition 3.2. If $X : \Omega \rightarrow \mathbb{R}$ is a σ -subgaussian random variable, then, for every $\delta \in (0, 1]$,

$$\begin{aligned}\mathbb{P}\left(X > -\sqrt{2\sigma^2 \log(1/\delta)}\right) &\geq 1 - \delta, \\ \mathbb{P}\left(X < \sqrt{2\sigma^2 \log(1/\delta)}\right) &\geq 1 - \delta, \\ \mathbb{P}\left(|X| < \sqrt{2\sigma^2 \log(2/\delta)}\right) &\geq 1 - \delta.\end{aligned}$$

Proof. These inequalities follow from Proposition 3.1 and the fact that $\mathbb{P}(F^c) = 1 - \mathbb{P}(F)$ for every $F \in \mathcal{F}$. □

Consider a sequence of independent random variables $(X_k : \Omega \rightarrow \mathbb{R} \mid k \in \mathbb{N}^+)$, each of which has the same law as a random variable $X \in \mathcal{L}^2(\Omega, \mathcal{F}, \mathbb{P})$ and let $\mu = \mathbb{E}(X)$.

Definition 3.1. For every $t \in \mathbb{N}^+$, the sample mean $M_t : \Omega \rightarrow \mathbb{R}$ after t observations is given by

$$M_t(\omega) = \frac{1}{t} \sum_{k=1}^t X_k(\omega).$$

Proposition 3.3. For every $t \in \mathbb{N}^+$, $\mathbb{E}(M_t) = \mu$ and $\text{Var}(M_t) = \text{Var}(X)/t$.

Proof. Recall that $\mathcal{L}^2(\Omega, \mathcal{F}, \mathbb{P})$ is a vector space over \mathbb{R} , so that $M_t \in \mathcal{L}^2(\Omega, \mathcal{F}, \mathbb{P})$. By the linearity of expectation,

$$\mathbb{E}(M_t) = \mathbb{E}\left(\frac{1}{t} \sum_{k=1}^t X_k\right) = \frac{1}{t} \sum_{k=1}^t \mathbb{E}(X_k) = \frac{1}{t} t \mu.$$

For every $c \in \mathbb{R}$ and $Y \in \mathcal{L}^2(\Omega, \mathcal{F}, \mathbb{P})$, recall that

$$\text{Var}(cY) = \mathbb{E}((cY)^2) - \mathbb{E}(cY)^2 = \mathbb{E}(c^2 Y^2) - (c\mathbb{E}(Y))^2 = c^2 \mathbb{E}(Y^2) - c^2 \mathbb{E}(Y)^2 = c^2 \text{Var}(Y).$$

Therefore, because the random variables $(X_k \mid k \in \mathbb{N}^+)$ are independent and identically distributed,

$$\text{Var}(M_t) = \text{Var}\left(\frac{1}{t} \sum_{k=1}^t X_k\right) = \frac{1}{t^2} \text{Var}\left(\sum_{k=1}^t X_k\right) = \frac{1}{t^2} \sum_{k=1}^t \text{Var}(X_k) = \frac{1}{t^2} t \text{Var}(X).$$

□

Proposition 3.4. For every $t \in \mathbb{N}^+$ and $\epsilon > 0$,

$$\mathbb{P}(|M_t - \mu| \geq \epsilon) \leq \frac{\text{Var}(X)}{t\epsilon^2}.$$

Proof. By Chebyshev's inequality, for every $\epsilon \geq 0$,

$$\frac{\text{Var}(X)}{t} = \text{Var}(M_t) = \mathbb{E}(|M_t - \mu|^2) \geq \epsilon^2 \mathbb{P}(|M_t - \mu| \geq \epsilon).$$

□

Proposition 3.5. If $X - \mu$ is a σ -subgaussian random variable, then, for every $t \in \mathbb{N}^+$ and $\epsilon > 0$,

$$\mathbb{P}(|M_t - \mu| \geq \epsilon) \leq \frac{\sigma^2}{t\epsilon^2}.$$

Proof. This proposition is a consequence of Proposition 2.3 and Proposition 3.4, since

$$\sigma^2 \geq \text{Var}(X - \mu) = \mathbb{E}((X - \mu)^2) - \mathbb{E}(X - \mu)^2 = \text{Var}(X) - (\mathbb{E}(X) - \mu)^2 = \text{Var}(X).$$

□

Proposition 3.6. If $X - \mu$ is a σ -subgaussian random variable, then, for every $t \in \mathbb{N}^+$ and $\epsilon \geq 0$,

$$\begin{aligned} \mathbb{P}(M_t \leq \mu - \epsilon) &\leq e^{-\frac{t\epsilon^2}{2\sigma^2}}, \\ \mathbb{P}(M_t \geq \mu + \epsilon) &\leq e^{-\frac{t\epsilon^2}{2\sigma^2}}, \\ \mathbb{P}(|M_t - \mu| \geq \epsilon) &\leq 2e^{-\frac{t\epsilon^2}{2\sigma^2}}. \end{aligned}$$

Proof. Recall that $\mathbb{E}(X - \mu) = 0$ and $\text{Var}(X - \mu) = \text{Var}(X)$. For every $t \in \mathbb{N}^+$,

$$M_t - \mu = \left(\frac{1}{t} \sum_{k=1}^t X_k\right) - \frac{1}{t} t \mu = \frac{1}{t} \sum_{k=1}^t (X_k - \mu).$$

Because $(X_k - \mu \mid k \in \mathbb{N}^+)$ are independent σ -subgaussian random variables, Proposition 2.5 guarantees that $\sum_{k=1}^t (X_k - \mu)$ is $(\sigma\sqrt{t})$ -subgaussian and Proposition 2.4 that $M_t - \mu$ is (σ/\sqrt{t}) -subgaussian. By Theorem 3.1,

$$\begin{aligned}\mathbb{P}(M_t - \mu \leq -\epsilon) &\leq e^{-\frac{\epsilon^2}{2(\sigma/\sqrt{t})^2}} = e^{-\frac{\epsilon^2}{2(\sigma^2/t)}} = e^{-\frac{t\epsilon^2}{2\sigma^2}}, \\ \mathbb{P}(M_t - \mu \geq \epsilon) &\leq e^{-\frac{\epsilon^2}{2(\sigma/\sqrt{t})^2}} = e^{-\frac{\epsilon^2}{2(\sigma^2/t)}} = e^{-\frac{t\epsilon^2}{2\sigma^2}}, \\ \mathbb{P}(|M_t - \mu| \geq \epsilon) &\leq 2e^{-\frac{\epsilon^2}{2(\sigma/\sqrt{t})^2}} = 2e^{-\frac{\epsilon^2}{2(\sigma^2/t)}} = 2e^{-\frac{t\epsilon^2}{2\sigma^2}}.\end{aligned}$$

□

Proposition 3.7. If $X - \mu$ is a σ -subgaussian random variable, then, for every $t \in \mathbb{N}^+$ and $\delta \in (0, 1]$,

$$\begin{aligned}\mathbb{P}\left(M_t \leq \mu - \sqrt{2\sigma^2 \log(1/\delta)/t}\right) &\leq \delta, \\ \mathbb{P}\left(M_t \geq \mu + \sqrt{2\sigma^2 \log(1/\delta)/t}\right) &\leq \delta, \\ \mathbb{P}(|M_t - \mu| \geq \sqrt{2\sigma^2 \log(2/\delta)/t}) &\leq \delta.\end{aligned}$$

Proof. Let $\delta \in (0, 1]$. If $\epsilon = \sqrt{2\sigma^2 \log(1/\delta)/t}$, then $\epsilon \geq 0$ and $\delta = e^{-\frac{t\epsilon^2}{2\sigma^2}}$, which implies the first two inequalities. If $\epsilon = \sqrt{2\sigma^2 \log(2/\delta)/t}$, then $\epsilon \geq 0$ and $\delta = 2e^{-\frac{t\epsilon^2}{2\sigma^2}}$, which implies the last inequality. □

Proposition 3.8. If $X - \mu$ is a σ -subgaussian random variable, then, for every $t \in \mathbb{N}^+$ and $\delta \in (0, 1]$,

$$\begin{aligned}\mathbb{P}\left(M_t > \mu - \sqrt{2\sigma^2 \log(1/\delta)/t}\right) &\geq 1 - \delta, \\ \mathbb{P}\left(M_t < \mu + \sqrt{2\sigma^2 \log(1/\delta)/t}\right) &\geq 1 - \delta, \\ \mathbb{P}(|M_t - \mu| < \sqrt{2\sigma^2 \log(2/\delta)/t}) &\geq 1 - \delta.\end{aligned}$$

Proof. These inequalities follow from Proposition 3.7 and the fact that $\mathbb{P}(F^c) = 1 - \mathbb{P}(F)$ for every $F \in \mathcal{F}$. □

Theorem 3.2 (Hoeffding's inequality). Consider a sequence of independent random variables $(Y_k : \Omega \rightarrow \mathbb{R} \mid k \in \mathbb{N}^+)$ and suppose that there are constants $a_k \in \mathbb{R}$ and $b_k \in \mathbb{R}$ such that $a_k < b_k$ and $\mathbb{P}(Y_k \in [a_k, b_k]) = 1$ for every $k \in \mathbb{N}^+$. In that case, for every $t \in \mathbb{N}^+$ and $\epsilon \geq 0$,

$$\mathbb{P}\left(\frac{1}{t} \sum_{k=1}^t (Y_k - \mathbb{E}(Y_k)) \geq \epsilon\right) \leq e^{-\frac{2t^2\epsilon^2}{\sum_{k=1}^t (b_k - a_k)^2}}.$$

Proof. For every $k \in \mathbb{N}^+$, note that $\mathbb{E}(Y_k - \mathbb{E}(Y_k)) = 0$ and $\mathbb{P}((Y_k - \mathbb{E}(Y_k)) \in [a_k - \mathbb{E}(Y_k), b_k - \mathbb{E}(Y_k)]) = 1$, so that $Y_k - \mathbb{E}(Y_k)$ is $(b_k - a_k)/2$ -subgaussian by Lemma 2.1. Because $(Y_k - \mathbb{E}(Y_k) \mid k \in \mathbb{N}^+)$ are independent random variables, Proposition 2.5 guarantees that $\sum_{k=1}^t (Y_k - \mathbb{E}(Y_k))$ is $\sqrt{\sum_{k=1}^t (b_k - a_k)^2/4}$ -subgaussian and Proposition 2.4 that $\sum_{k=1}^t (Y_k - \mathbb{E}(Y_k))/t$ is $\sqrt{\sum_{k=1}^t (b_k - a_k)^2/(4t^2)}$ -subgaussian. By Theorem 3.1,

$$\mathbb{P}\left(\frac{1}{t} \sum_{k=1}^t (Y_k - \mathbb{E}(Y_k)) \geq \epsilon\right) \leq e^{-\frac{\epsilon^2}{2(\sqrt{\sum_{k=1}^t (b_k - a_k)^2/(4t^2)})^2}} = e^{-\frac{\epsilon^2}{\frac{1}{2t^2} \sum_{k=1}^t (b_k - a_k)^2}} = e^{-\frac{2t^2\epsilon^2}{\sum_{k=1}^t (b_k - a_k)^2}}.$$

□

Theorem 3.3 (Bretagnolle-Huber-Carol inequality). Suppose that there is an $m \in \mathbb{N}^+$ such that $X(\omega) \in \{1, \dots, m\}$ for every $\omega \in \Omega$. Consider a vector $p \in [0, 1]^m$ such that $p_i = \mathbb{P}(X = i)$ for every $i \in \{1, \dots, m\}$ and a random vector $P_t : \Omega \rightarrow [0, 1]^m$ such that $P_{t,i} = 1/t \sum_{k=1}^t \mathbb{I}_{\{X_k = i\}}$ for every $t \in \mathbb{N}^+$ and $i \in \{1, \dots, m\}$. For every $\delta \in (0, 1]$,

$$\mathbb{P}\left(\|P_t - p\|_1 \geq \sqrt{2(\log(1/\delta) + m \log(2))/t}\right) \leq \delta.$$

Proof. Recall that $|a| = \max(a, -a)$ for every $a \in \mathbb{R}$. Therefore, for every $t \in \mathbb{N}^+$,

$$\|P_t - p\|_1 = \sum_{i=1}^m |P_{t,i} - p_i| = \sum_{i=1}^m \max_{\lambda_i \in \{-1,1\}} \lambda_i (P_{t,i} - p_i) = \max_{\lambda \in \{-1,1\}^m} \sum_{i=1}^m \lambda_i (P_{t,i} - p_i).$$

For every $t \in \mathbb{N}^+$, by expanding the previous expression and exchanging the order of the summations,

$$\|P_t - p\|_1 = \max_{\lambda \in \{-1,1\}^m} \sum_{i=1}^m \lambda_i \left(\frac{1}{t} \sum_{k=1}^t \mathbb{I}_{\{X_k=i\}} - \frac{1}{t} \sum_{k=1}^t p_i \right) = \max_{\lambda \in \{-1,1\}^m} \frac{1}{t} \sum_{k=1}^t \sum_{i=1}^m \lambda_i \mathbb{I}_{\{X_k=i\}} - \lambda_i p_i.$$

For every $k \in \{1, \dots, t\}$ and $\lambda \in \{-1,1\}^m$, let $Y_k^{(\lambda)} = \sum_{i=1}^m \lambda_i \mathbb{I}_{\{X_k=i\}} = \lambda_{X_k}$, so that $|Y_k^{(\lambda)}| \leq 1$ and

$$\mathbb{E} \left(Y_k^{(\lambda)} \right) = \mathbb{E} \left(\sum_{i=1}^m \lambda_i \mathbb{I}_{\{X_k=i\}} \right) = \sum_{i=1}^m \lambda_i \mathbb{P}(X_k = i) = \sum_{i=1}^m \lambda_i \mathbb{P}(X = i) = \sum_{i=1}^m \lambda_i p_i.$$

For every $t \in \mathbb{N}^+$, by rewriting a previous expression,

$$\|P_t - p\|_1 = \max_{\lambda \in \{-1,1\}^m} \frac{1}{t} \sum_{k=1}^t \left(Y_k^{(\lambda)} - \mathbb{E} \left(Y_k^{(\lambda)} \right) \right).$$

Therefore, for every $t \in \mathbb{N}^+$ and $\epsilon \geq 0$,

$$\{\|P_t - p\|_1 \geq \epsilon\} = \left\{ \max_{\lambda \in \{-1,1\}^m} \frac{1}{t} \sum_{k=1}^t \left(Y_k^{(\lambda)} - \mathbb{E} \left(Y_k^{(\lambda)} \right) \right) \geq \epsilon \right\} = \bigcup_{\lambda \in \{-1,1\}^m} \left\{ \frac{1}{t} \sum_{k=1}^t \left(Y_k^{(\lambda)} - \mathbb{E} \left(Y_k^{(\lambda)} \right) \right) \geq \epsilon \right\}.$$

By employing a union bound, Theorem 3.2, and the fact that the set $\{-1,1\}^m$ has 2^m elements,

$$\mathbb{P}(\|P_t - p\|_1 \geq \epsilon) \leq \sum_{\lambda \in \{-1,1\}^m} \mathbb{P} \left(\frac{1}{t} \sum_{k=1}^t \left(Y_k^{(\lambda)} - \mathbb{E} \left(Y_k^{(\lambda)} \right) \right) \geq \epsilon \right) \leq \sum_{\lambda \in \{-1,1\}^m} e^{-\frac{t\epsilon^2}{2}} = 2^m e^{-\frac{t\epsilon^2}{2}}$$

Let $\delta \in (0, 1]$. If $\epsilon = \sqrt{2(\log(1/\delta) + m \log(2)) / t}$, then $\epsilon \geq 0$ and $\delta = 2^m e^{-\frac{t\epsilon^2}{2}}$. Therefore,

$$\mathbb{P} \left(\|P_t - p\|_1 \geq \sqrt{2(\log(1/\delta) + m \log(2)) / t} \right) \leq \delta.$$

□

4 Stochastic bandits

Definition 4.1. A set of actions \mathcal{A} is a non-empty subset of \mathbb{N} .

Definition 4.2. For a set of actions \mathcal{A} , consider a sequence of probability measures $\nu = (P_a \mid a \in \mathcal{A})$ on the measurable space $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$. If $h : \mathbb{R} \rightarrow \mathbb{R}$ is a $\mathcal{B}(\mathbb{R})$ -measurable function and there is a constant $c \in [0, \infty)$ such that $\int_{\mathbb{R}} |h(x)| P_a(dx) \leq c$ for every action $a \in \mathcal{A}$, then h is ν -integrable.

Definition 4.3. For a set of actions \mathcal{A} , consider a sequence of probability measures $\nu = (P_a \mid a \in \mathcal{A})$ on the measurable space $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$. If the identity function is ν -integrable, the mean μ_a^ν of action a is defined by $\mu_a^\nu = \int_{\mathbb{R}} x P_a(dx)$ and the supremum mean μ_*^ν is defined by $\mu_*^\nu = \sup_a \mu_a^\nu$. If $\mu_a^\nu = \mu_*^\nu$ for some action $a \in \mathcal{A}$, then ν is a stochastic bandit for the set of actions \mathcal{A} .

Proposition 4.1. If $\nu = (P_a \mid a \in \mathcal{A})$ is a stochastic bandit for the set of actions \mathcal{A} , then there is a constant $c \in [0, \infty)$ such that $\mu_a^\nu \in [-c, c]$ for every action $a \in \mathcal{A}$.

Proof. Since the identity function is ν -integrable, there is a constant $c \in [0, \infty)$ such that $\int_{\mathbb{R}} |x| P_a(dx) \leq c$ for every action $a \in \mathcal{A}$. Therefore, $|\mu_a^\nu| = \left| \int_{\mathbb{R}} x P_a(dx) \right| \leq \int_{\mathbb{R}} |x| P_a(dx) \leq c$ for every action $a \in \mathcal{A}$. \square

Definition 4.4. For a set of actions \mathcal{A} , a policy π is a sequence of functions $(\pi_t : \mathbb{R}^t \rightarrow \mathcal{A} \mid t \in \mathbb{N}^+)$, where the so-called policy π_t for time step t is $\mathcal{B}(\mathbb{R}^t)$ -measurable.

Proposition 4.2. For a set of actions \mathcal{A} , a stochastic bandit $\nu = (P_a \mid a \in \mathcal{A})$, and a policy $\pi = (\pi_t \mid t \in \mathbb{N}^+)$, there is a probability triple $(\Omega, \mathcal{F}, \mathbb{P})$ carrying a stochastic process $(X_t : \Omega \rightarrow \mathbb{R} \mid t \in \mathbb{N})$ such that $\mathbb{E}(|X_t|) < \infty$ and

$$\mathbb{P}(X_t \in B \mid X_0, \dots, X_{t-1}) = P_{A_t}(B)$$

almost surely for every $t \in \mathbb{N}^+$ and $B \in \mathcal{B}(\mathbb{R})$, where $A_t = \pi_t(X_0, \dots, X_{t-1})$. Additionally, if a function $h : \mathbb{R} \rightarrow \mathbb{R}$ is ν -integrable, then $\mathbb{E}(|h(X_t)|) < \infty$ for every $t \in \mathbb{N}^+$.

Proof. By Kolmogorov's extension theorem, there is a probability triple $(\Omega, \mathcal{F}, \mathbb{P})$ carrying a countable set of independent random variables $\{Z_{t,a} : \Omega \rightarrow \mathbb{R} \mid t \in \mathbb{N}^+ \text{ and } a \in \mathcal{A}\}$ such that $\mathbb{P}(Z_{t,a} \in B) = P_a(B)$ for every $t \in \mathbb{N}^+$, $a \in \mathcal{A}$, and $B \in \mathcal{B}(\mathbb{R})$. For every $t \in \mathbb{N}^+$, let $A_t : \Omega \rightarrow \mathcal{A}$ and $X_t : \Omega \rightarrow \mathbb{R}$ be given by

$$\begin{aligned} A_t(\omega) &= \pi_t(X_0(\omega), \dots, X_{t-1}(\omega)), \\ X_t(\omega) &= Z_{t, A_t(\omega)}(\omega) = \sum_a \mathbb{I}_{\{A_t=a\}}(\omega) Z_{t,a}(\omega), \end{aligned}$$

where $X_0 : \Omega \rightarrow \mathbb{R}$ is given by $X_0(\omega) = 0$.

For every $t \in \mathbb{N}^+$, let $\mathcal{F}_{t-1} = \sigma\left(\bigcup_{k < t, a} \sigma(Z_{k,a})\right)$. For every $t \in \mathbb{N}^+$ and $a \in \mathcal{A}$, note that $\sigma(\mathbb{I}_{\{A_t=a\}}) \subseteq \sigma(A_t) \subseteq \sigma(X_0, \dots, X_{t-1}) \subseteq \mathcal{F}_{t-1}$. Because \mathcal{F}_{t-1} and $\sigma(Z_{t,a})$ are independent, so are $\mathbb{I}_{\{A_t=a\}}$ and $Z_{t,a}$.

Therefore, if a function $h : \mathbb{R} \rightarrow \mathbb{R}$ is ν -integrable, then $\mathbb{E}(|h(X_t)|) < \infty$ for every $t \in \mathbb{N}^+$, since

$$\mathbb{E}(|h(X_t)|) = \sum_a \mathbb{E}(\mathbb{I}_{\{A_t=a\}} |h(Z_{t,a})|) = \sum_a \mathbb{E}(\mathbb{I}_{\{A_t=a\}}) \mathbb{E}(|h(Z_{t,a})|) = \sum_a \mathbb{P}(A_t = a) \int_{\mathbb{R}} |h(x)| P_a(dx) \leq c < \infty.$$

In particular, because the identity function is ν -integrable, $\mathbb{E}(|X_t|) < \infty$ for every $t \in \mathbb{N}^+$.

By definition, almost surely for every $t \in \mathbb{N}^+$ and $B \in \mathcal{B}(\mathbb{R})$,

$$\mathbb{P}(X_t \in B \mid X_0, \dots, X_{t-1}) = \mathbb{E}(\mathbb{I}_{\{X_t \in B\}} \mid \sigma(X_0, \dots, X_{t-1})).$$

For every $t \in \mathbb{N}^+$ and $B \in \mathcal{B}(\mathbb{R})$, note that $\{X_t \in B\} = \bigcup_a \{A_t = a\} \cap \{Z_{t,a} \in B\}$. Therefore, almost surely,

$$\mathbb{P}(X_t \in B \mid X_0, \dots, X_{t-1}) = \sum_a \mathbb{E}(\mathbb{I}_{\{A_t=a\}} \mathbb{I}_{\{Z_{t,a} \in B\}} \mid \sigma(X_0, \dots, X_{t-1})).$$

For every $t \in \mathbb{N}^+$ and $a \in \mathcal{A}$, recall that $\mathbb{I}_{\{A_t=a\}}$ is $\sigma(X_0, \dots, X_{t-1})$ -measurable. Therefore, almost surely,

$$\mathbb{P}(X_t \in B \mid X_0, \dots, X_{t-1}) = \sum_a \mathbb{I}_{\{A_t=a\}} \mathbb{E}(\mathbb{I}_{\{Z_{t,a} \in B\}} \mid \sigma(X_0, \dots, X_{t-1})).$$

Since $\sigma(X_0, \dots, X_{t-1}) \subseteq \mathcal{F}_{t-1}$ and $\sigma(\mathbb{I}_{\{Z_{t,a} \in B\}}) \subseteq \sigma(Z_{t,a})$ are independent, almost surely,

$$\mathbb{P}(X_t \in B \mid X_0, \dots, X_{t-1}) = \sum_a \mathbb{I}_{\{A_t=a\}} \mathbb{E}(\mathbb{I}_{\{Z_{t,a} \in B\}}) = \sum_a \mathbb{I}_{\{A_t=a\}} P_a(B) = P_{A_t}(B).$$

\square

Definition 4.5. The canonical space (Ω, \mathcal{F}) that carries the reward process $X = (X_t \mid t \in \mathbb{N})$ is a measurable space such that $\Omega = \mathbb{R}^\infty$. Furthermore, for every $t \in \mathbb{N}$, the function $X_t : \Omega \rightarrow \mathbb{R}$ is given by $X_t(\omega) = \omega_t$ and the σ -algebra \mathcal{F} on Ω is given by $\mathcal{F} = \sigma(X_0, X_1, \dots)$.

Theorem 4.1. For every set of actions \mathcal{A} , stochastic bandit $\nu = (P_a \mid a \in \mathcal{A})$, and policy $\pi = (\pi_t \mid t \in \mathbb{N}^+)$, there is a probability measure $\mathbb{P}^{\nu, \pi}$ on the canonical space (Ω, \mathcal{F}) that carries the reward process $X = (X_t \mid t \in \mathbb{N})$ such that $\mathbb{E}^{\nu, \pi}(|X_t|) < \infty$ and

$$\mathbb{P}^{\nu, \pi}(X_t \in B \mid X_0, \dots, X_{t-1}) = P_{A_t}(B)$$

almost surely for every $t \in \mathbb{N}^+$ and $B \in \mathcal{B}(\mathbb{R})$, where $A_t = \pi_t(X_0, \dots, X_{t-1})$. Additionally, if a function $h : \mathbb{R} \rightarrow \mathbb{R}$ is ν -integrable, then $\mathbb{E}^{\nu, \pi}(|h(X_t)|) < \infty$ for every $t \in \mathbb{N}^+$. The probability triple $(\Omega, \mathcal{F}, \mathbb{P}^{\nu, \pi})$ is called a canonical triple for the stochastic bandit ν under the policy π .

Proof. Proposition 4.2 ensures that there is a probability triple $(\tilde{\Omega}^{\nu, \pi}, \tilde{\mathcal{F}}^{\nu, \pi}, \tilde{\mathbb{P}}^{\nu, \pi})$ carrying a stochastic process $(\tilde{X}_t^{\nu, \pi} : \tilde{\Omega}^{\nu, \pi} \rightarrow \mathbb{R} \mid t \in \mathbb{N})$ such that, almost surely,

$$\tilde{\mathbb{P}}^{\nu, \pi}(\tilde{X}_t^{\nu, \pi} \in B \mid \tilde{X}_0^{\nu, \pi}, \dots, \tilde{X}_{t-1}^{\nu, \pi}) = P_{\tilde{A}_t}(B)$$

for every $t \in \mathbb{N}^+$ and $B \in \mathcal{B}(\mathbb{R})$, where $\tilde{A}_t = \pi_t(\tilde{X}_0^{\nu, \pi}, \dots, \tilde{X}_{t-1}^{\nu, \pi})$.

Consider the function $\tilde{X}^{\nu, \pi} : \tilde{\Omega}^{\nu, \pi} \rightarrow \Omega$ given by $\tilde{X}^{\nu, \pi}(\tilde{\omega}) = (\tilde{X}_t^{\nu, \pi}(\tilde{\omega}) \mid t \in \mathbb{N})$. The function $\tilde{X}^{\nu, \pi}$ is $\tilde{\mathcal{F}}^{\nu, \pi}/\mathcal{F}$ -measurable, so that the function $\mathbb{P}^{\nu, \pi} : \mathcal{F} \rightarrow [0, 1]$ defined by

$$\mathbb{P}^{\nu, \pi}(F) = \tilde{\mathbb{P}}^{\nu, \pi}\left(\left(\tilde{X}^{\nu, \pi}\right)^{-1}(F)\right) = \tilde{\mathbb{P}}^{\nu, \pi}\left(\{\tilde{\omega} \in \tilde{\Omega}^{\nu, \pi} \mid \tilde{X}^{\nu, \pi}(\tilde{\omega}) \in F\}\right)$$

is a probability measure on the measurable space (Ω, \mathcal{F}) .

In order to show that $\tilde{X}^{\nu, \pi}$ is $\sigma(\tilde{X}_0^{\nu, \pi}, \dots, \tilde{X}_t^{\nu, \pi})/\sigma(X_0, \dots, X_t)$ -measurable for every $t \in \mathbb{N}^+$, let \mathcal{I}_t be given by

$$\mathcal{I}_t = \left\{ \bigcap_{k=0}^t \{X_k \in B_k\} \mid B_k \in \mathcal{B}(\mathbb{R}) \text{ for every } k \in \{0, \dots, t\} \right\},$$

so that \mathcal{I}_t is a π -system on Ω such that $\sigma(\mathcal{I}_t) = \sigma(X_0, \dots, X_t)$. For every $t \in \mathbb{N}^+$ and $I_t \in \mathcal{I}_t$,

$$(\tilde{X}^{\nu, \pi})^{-1}(I_t) = (\tilde{X}^{\nu, \pi})^{-1}\left(\bigcap_{k=0}^t \{X_k \in B_k\}\right) = \bigcap_{k=0}^t (\tilde{X}^{\nu, \pi})^{-1}(\{X_k \in B_k\}) = \bigcap_{k=0}^t \{\tilde{X}_k^{\nu, \pi} \in B_k\},$$

which uses the fact that

$$(\tilde{X}^{\nu, \pi})^{-1}(\{X_k \in B_k\}) = \left\{ \tilde{\omega} \in \tilde{\Omega}^{\nu, \pi} \mid \tilde{X}^{\nu, \pi}(\tilde{\omega}) \in \{\omega \in \Omega \mid \omega_k \in B_k\} \right\} = \{\tilde{X}_k^{\nu, \pi} \in B_k\}.$$

Since $(\tilde{X}^{\nu, \pi})^{-1}(I_t) \in \sigma(\tilde{X}_0^{\nu, \pi}, \dots, \tilde{X}_t^{\nu, \pi})$ for every $I_t \in \mathcal{I}_t$, $\tilde{X}^{\nu, \pi}$ is $\sigma(\tilde{X}_0^{\nu, \pi}, \dots, \tilde{X}_t^{\nu, \pi})/\sigma(X_0, \dots, X_t)$ -measurable. For every $t \in \mathbb{N}^+$ and $H_{t-1} \in \sigma(X_0, \dots, X_{t-1})$, let $\tilde{H}_{t-1} = (\tilde{X}^{\nu, \pi})^{-1}(H_{t-1})$. For every $B \in \mathcal{B}(\mathbb{R})$,

$$\mathbb{E}^{\nu, \pi}(\mathbb{I}_{\{X_t \in B\}} \mathbb{I}_{H_{t-1}}) = \mathbb{P}^{\nu, \pi}(\{X_t \in B\} \cap H_{t-1}) = \tilde{\mathbb{P}}^{\nu, \pi}\left((\tilde{X}^{\nu, \pi})^{-1}(\{X_t \in B\}) \cap (\tilde{X}^{\nu, \pi})^{-1}(H_{t-1})\right).$$

Because $\tilde{H}_{t-1} \in \sigma(\tilde{X}_0^{\nu, \pi}, \dots, \tilde{X}_{t-1}^{\nu, \pi})$,

$$\mathbb{E}^{\nu, \pi}(\mathbb{I}_{\{X_t \in B\}} \mathbb{I}_{H_{t-1}}) = \tilde{\mathbb{P}}^{\nu, \pi}\left(\{\tilde{X}_t^{\nu, \pi} \in B\} \cap \tilde{H}_{t-1}\right) = \tilde{\mathbb{E}}^{\nu, \pi}\left(\mathbb{I}_{\{\tilde{X}_t^{\nu, \pi} \in B\}} \mathbb{I}_{\tilde{H}_{t-1}}\right) = \tilde{\mathbb{E}}^{\nu, \pi}\left(P_{\tilde{A}_t}(B) \mathbb{I}_{\tilde{H}_{t-1}}\right),$$

where $\tilde{A}_t = \pi_t(\tilde{X}_0^{\nu, \pi}, \dots, \tilde{X}_{t-1}^{\nu, \pi})$. Therefore,

$$\mathbb{E}^{\nu, \pi}(\mathbb{I}_{\{X_t \in B\}} \mathbb{I}_{H_{t-1}}) = \tilde{\mathbb{E}}^{\nu, \pi}\left(\sum_a \mathbb{I}_{\{\tilde{A}_t = a\}} P_a(B) \mathbb{I}_{\tilde{H}_{t-1}}\right) = \sum_a P_a(B) \tilde{\mathbb{P}}^{\nu, \pi}\left(\{\tilde{A}_t = a\} \cap \tilde{H}_{t-1}\right).$$

For every $a \in \mathcal{A}$, note that $\mathbb{P}^{\nu, \pi}(\{A_t = a\} \cap H_{t-1})$ is given by

$$\mathbb{P}^{\nu, \pi}(\{A_t = a\} \cap H_{t-1}) = \tilde{\mathbb{P}}^{\nu, \pi}\left((\tilde{X}^{\nu, \pi})^{-1}(\{A_t = a\}) \cap (\tilde{X}^{\nu, \pi})^{-1}(H_{t-1})\right) = \tilde{\mathbb{P}}^{\nu, \pi}\left(\{\tilde{A}_t = a\} \cap \tilde{H}_{t-1}\right),$$

which uses the fact that

$$(\tilde{X}^{\nu,\pi})^{-1}(\{A_t = a\}) = \{\tilde{\omega} \in \tilde{\Omega}^{\nu,\pi} \mid \tilde{X}^{\nu,\pi}(\tilde{\omega}) \in \{\omega \in \Omega \mid \pi_t(\omega_0, \dots, \omega_{t-1}) = a\}\} = \{\tilde{A}_t = a\}.$$

Finally, for every $t \in \mathbb{N}^+$, $H_{t-1} \in \sigma(X_0, \dots, X_{t-1})$, $B \in \mathcal{B}(\mathbb{R})$,

$$\mathbb{E}^{\nu,\pi}(\mathbb{I}_{\{X_t \in B\}} \mathbb{I}_{H_{t-1}}) = \sum_a P_a(B) \mathbb{P}^{\nu,\pi}(\{A_t = a\} \cap H_{t-1}) = \mathbb{E}^{\nu,\pi}(P_{A_t}(B) \mathbb{I}_{H_{t-1}}).$$

Because $P_{A_t}(B)$ is $\sigma(X_0, \dots, X_{t-1})$ -measurable, almost surely,

$$\mathbb{P}^{\nu,\pi}(X_t \in B \mid X_0, \dots, X_{t-1}) = \mathbb{E}^{\nu,\pi}(\mathbb{I}_{\{X_t \in B\}} \mid \sigma(X_0, \dots, X_{t-1})) = P_{A_t}(B).$$

For every $t \in \mathbb{N}^+$, consider the law $\mathcal{L}_t : \mathcal{B}(\mathbb{R}) \rightarrow [0, 1]$ given by

$$\mathcal{L}_t(B) = \mathbb{P}^{\nu,\pi}(X_t \in B) = \tilde{\mathbb{P}}^{\nu,\pi}((\tilde{X}^{\nu,\pi})^{-1}(\{X_t \in B\})) = \tilde{\mathbb{P}}^{\nu,\pi}(\tilde{X}_t^{\nu,\pi} \in B).$$

If a function $h : \mathbb{R} \rightarrow \mathbb{R}$ is ν -integrable, then $\mathbb{E}^{\nu,\pi}(|h(X_t)|) < \infty$ for every $t \in \mathbb{N}^+$, since

$$\mathbb{E}^{\nu,\pi}(|h(X_t)|) = \int_{\mathbb{R}} |h(x)| \mathcal{L}_t(dx) = \tilde{\mathbb{E}}^{\nu,\pi}(|h(\tilde{X}_t^{\nu,\pi})|) < \infty.$$

In particular, because the identity function is ν -integrable, $\mathbb{E}^{\nu,\pi}(|X_t|) < \infty$ for every $t \in \mathbb{N}^+$. □

For the remaining, consider a set of actions \mathcal{A} , a stochastic bandit $\nu = (P_a \mid a \in \mathcal{A})$, a policy $\pi = (\pi_t \mid t \in \mathbb{N}^+)$, and let $(\Omega, \mathcal{F}, \mathbb{P}^{\nu,\pi})$ be a canonical triple for the stochastic bandit ν under the policy π .

Proposition 4.3. For every $t \in \mathbb{N}^+$, if a function $h : \mathbb{R} \rightarrow \mathbb{R}$ is ν -integrable, then

$$\mathbb{E}^{\nu,\pi}(h(X_t) \mid X_0, \dots, X_{t-1}) = \sum_a \mathbb{I}_{\{A_t=a\}} \int_{\mathbb{R}} h(x) P_a(dx)$$

almost surely, where $A_t = \pi_t(X_0, \dots, X_{t-1})$.

Proof. Since the function $h : \mathbb{R} \rightarrow \mathbb{R}$ is ν -integrable, recall that $\mathbb{E}^{\nu,\pi}(|h(X_t)|) < \infty$ for every $t \in \mathbb{N}^+$.

First, suppose that $h = \mathbb{I}_B$ for some $B \in \mathcal{B}(\mathbb{R})$. Because $\mathbb{I}_B(X_t) = \mathbb{I}_{\{X_t \in B\}}$, almost surely,

$$\mathbb{E}^{\nu,\pi}(\mathbb{I}_B(X_t) \mid X_0, \dots, X_{t-1}) = P_{A_t}(B) = \sum_a \mathbb{I}_{\{A_t=a\}} P_a(B) = \sum_a \mathbb{I}_{\{A_t=a\}} \int_{\mathbb{R}} \mathbb{I}_B(x) P_a(dx).$$

Next, suppose that h is a simple function that can be written as $h = \sum_{k=1}^m b_k \mathbb{I}_{B_k}$ for some fixed $b_1, b_2, \dots, b_m \in [0, \infty]$ and $B_1, B_2, \dots, B_m \in \mathcal{B}(\mathbb{R})$. Almost surely,

$$\mathbb{E}^{\nu,\pi}\left(\sum_{k=1}^m b_k \mathbb{I}_{B_k}(X_t) \mid X_0, \dots, X_{t-1}\right) = \sum_{k=1}^m b_k \sum_a \mathbb{I}_{\{A_t=a\}} \int_{\mathbb{R}} \mathbb{I}_{B_k}(x) P_a(dx) = \sum_a \mathbb{I}_{\{A_t=a\}} \int_{\mathbb{R}} \sum_{k=1}^m b_k \mathbb{I}_{B_k}(x) P_a(dx).$$

Next, suppose that h is a non-negative $\mathcal{B}(\mathbb{R})$ -measurable function. For any $k \in \mathbb{N}$, consider the simple function $h_k = \alpha_k \circ h$, where α_k is the k -th staircase function. Almost surely, since $h_k(X_t) \uparrow h(X_t)$,

$$\mathbb{E}^{\nu,\pi}(h(X_t) \mid X_0, \dots, X_{t-1}) = \mathbb{E}^{\nu,\pi}\left(\lim_{k \rightarrow \infty} h_k(X_t) \mid X_0, \dots, X_{t-1}\right) = \lim_{k \rightarrow \infty} \mathbb{E}^{\nu,\pi}(h_k(X_t) \mid X_0, \dots, X_{t-1}).$$

Since $h_k \uparrow h$, by the monotone-convergence theorem, almost surely,

$$\mathbb{E}^{\nu,\pi}(h(X_t) \mid X_0, \dots, X_{t-1}) = \lim_{k \rightarrow \infty} \sum_a \mathbb{I}_{\{A_t=a\}} \int_{\mathbb{R}} h_k(x) P_a(dx) = \sum_a \mathbb{I}_{\{A_t=a\}} \int_{\mathbb{R}} \lim_{k \rightarrow \infty} h_k(x) P_a(dx).$$

Finally, suppose that $h = h^+ - h^-$ is a $\mathcal{B}(\mathbb{R})$ -measurable function. Almost surely,

$$\mathbb{E}^{\nu,\pi}(h(X_t) \mid X_0, \dots, X_{t-1}) = \left(\sum_a \mathbb{I}_{\{A_t=a\}} \int_{\mathbb{R}} h^+(x) P_a(dx)\right) - \left(\sum_a \mathbb{I}_{\{A_t=a\}} \int_{\mathbb{R}} h^-(x) P_a(dx)\right).$$

By the linearity of the integral, almost surely,

$$\mathbb{E}^{\nu, \pi} (h(X_t) \mid X_0, \dots, X_{t-1}) = \sum_a \mathbb{I}_{\{A_t=a\}} \int_{\mathbb{R}} (h^+(x) - h^-(x)) P_a(dx) = \sum_a \mathbb{I}_{\{A_t=a\}} \int_{\mathbb{R}} h(x) P_a(dx).$$

□

Proposition 4.4. If $t \in \mathbb{N}^+$ and $A_t = \pi_t(X_0, \dots, X_{t-1})$, then $\mathbb{E}^{\nu, \pi} (X_t \mid A_t) = \mu_{A_t}^{\nu}$ almost surely.

Proof. For every $t \in \mathbb{N}^+$, $\mathbb{E}^{\nu, \pi} (|X_t|) < \infty$ and A_t is $\sigma(X_0, \dots, X_{t-1})$ -measurable. Therefore, almost surely,

$$\mathbb{E}^{\nu, \pi} (X_t \mid A_t) = \mathbb{E}^{\nu, \pi} (\mathbb{E}^{\nu, \pi} (X_t \mid X_0, \dots, X_{t-1}) \mid A_t) = \sum_a \mathbb{I}_{\{A_t=a\}} \int_{\mathbb{R}} x P_a(dx) = \sum_a \mathbb{I}_{\{A_t=a\}} \mu_a^{\nu} = \mu_{A_t}^{\nu},$$

by the tower property, Proposition 4.3 applied to the identity function, and taking out what is known. □

Proposition 4.5. If $t \in \mathbb{N}^+$ and $A_t = \pi_t(X_0, \dots, X_{t-1})$, then

$$\mathbb{E}^{\nu, \pi} (X_t) = \mathbb{E}^{\nu, \pi} (\mathbb{E}^{\nu, \pi} (X_t \mid A_t)) = \mathbb{E}^{\nu, \pi} (\mu_{A_t}^{\nu}) = \sum_a \mu_a^{\nu} \mathbb{P}^{\nu, \pi} (A_t = a).$$

Definition 4.6. For every $t \in \mathbb{N}^+$, the total reward S_t after t time steps is given by $S_t = \sum_{k=1}^t X_k$.

Definition 4.7. For every $t \in \mathbb{N}^+$, the regret $R_t^{\nu, \pi}$ of policy π on ν after t time steps is given by

$$R_t^{\nu, \pi} = t\mu_*^{\nu} - \sum_{k=1}^t \mathbb{E}^{\nu, \pi} (X_k).$$

Definition 4.8. For every action $a \in \mathcal{A}$, the suboptimality gap is defined by $\Delta_a^{\nu} = \mu_*^{\nu} - \mu_a^{\nu}$, so that $\Delta_a^{\nu} \geq 0$.

Definition 4.9. The number of times $T_{t,a}^{\pi} : \Omega \rightarrow \{0, \dots, t\}$ that policy π selects $a \in \mathcal{A}$ by time $t \in \mathbb{N}^+$ is given by

$$T_{t,a}^{\pi}(\omega) = \sum_{k=1}^t \mathbb{I}_{\{A_k=a\}}(\omega),$$

where $A_k = \pi_k(X_0, \dots, X_{k-1})$ for every $k \leq t$. Note that $\sum_a T_{t,a}^{\pi}(\omega) = t$ for every $\omega \in \Omega$.

Definition 4.10. The average reward $M_{t,a}^{\pi} : \Omega \rightarrow \mathbb{R}$ that policy π observes for $a \in \mathcal{A}$ by time $t \in \mathbb{N}^+$ is given by

$$M_{t,a}^{\pi}(\omega) = \frac{1}{T_{t,a}^{\pi}(\omega)} \sum_{k=1}^t X_k(\omega) \mathbb{I}_{\{A_k=a\}}(\omega)$$

whenever $T_{t,a}^{\pi}(\omega) > 0$, where $A_k = \pi_k(X_0, \dots, X_{k-1})$ for every $k \leq t$.

Theorem 4.2. For every $t \in \mathbb{N}^+$, the regret $R_t^{\nu, \pi}$ of policy π on ν after t time steps is given by

$$R_t^{\nu, \pi} = \sum_a \Delta_a^{\nu} \mathbb{E}^{\nu, \pi} (T_{t,a}^{\pi}).$$

Proof. For every $t \in \mathbb{N}^+$, let $A_k = \pi_k(X_0, \dots, X_{k-1})$ for every $k \leq t$, so that $\mathbb{E}^{\nu, \pi} (T_{t,a}^{\pi}) = \sum_{k=1}^t \mathbb{P}^{\nu, \pi} (A_k = a)$ and

$$\sum_a \mathbb{E}^{\nu, \pi} (T_{t,a}^{\pi}) = \sum_a \sum_{k=1}^t \mathbb{P}^{\nu, \pi} (A_k = a) = \sum_{k=1}^t \sum_a \mathbb{P}^{\nu, \pi} (A_k = a) = t.$$

By the definition of the regret $R_t^{\nu, \pi}$ of policy π on ν after t time steps,

$$R_t^{\nu, \pi} = t\mu_*^{\nu} - \sum_{k=1}^t \mathbb{E}^{\nu, \pi} (X_k) = \sum_{k=1}^t \sum_a \mu_*^{\nu} \mathbb{P}^{\nu, \pi} (A_k = a) - \sum_{k=1}^t \sum_a \mu_a^{\nu} \mathbb{P}^{\nu, \pi} (A_k = a).$$

By rearranging terms and the definition of suboptimality gap,

$$R_t^{\nu, \pi} = \sum_{k=1}^t \sum_a (\mu_*^{\nu} - \mu_a^{\nu}) \mathbb{P}^{\nu, \pi} (A_k = a) = \sum_a \Delta_a^{\nu} \sum_{k=1}^t \mathbb{P}^{\nu, \pi} (A_k = a) = \sum_a \Delta_a^{\nu} \mathbb{E}^{\nu, \pi} (T_{t,a}^{\pi}).$$

□

Proposition 4.6. If $t \in \mathbb{N}^+$, then $R_t^{\nu, \pi} \geq 0$.

Proof. Since $\Delta_a^\nu \geq 0$ and $\mathbb{E}^{\nu, \pi}(T_{t,a}^\pi) \geq 0$ for every $a \in \mathcal{A}$ and $t \in \mathbb{N}^+$, the claim is a consequence of Theorem 4.2. \square

Proposition 4.7. Consider an action $a^* \in \mathcal{A}$ such that $\mu_{a^*}^\nu = \mu_*^\nu$. If $\pi_t = a^*$ for every $t \in \mathbb{N}^+$, then $R_t^{\nu, \pi} = 0$.

Proof. For every $t \in \mathbb{N}^+$, note that $T_{t,a}^\pi = 0$ for every $a \neq a^*$. Therefore,

$$R_t^{\nu, \pi} = \sum_a \Delta_a^\nu \mathbb{E}^{\nu, \pi}(T_{t,a}^\pi) = \Delta_{a^*}^\nu \mathbb{E}^{\nu, \pi}(T_{t,a^*}^\pi) = (\mu_*^\nu - \mu_{a^*}^\nu) \mathbb{E}^{\nu, \pi}(T_{t,a^*}^\pi) = 0.$$

\square

Proposition 4.8. For every $t \in \mathbb{N}^+$, let $A_k = \pi_k(X_0, \dots, X_{k-1})$ for every $k \leq t$. If $R_t^{\nu, \pi} = 0$, then $\mu_{A_k}^\nu = \mu_*^\nu$ almost surely for every $k \leq t$.

Proof. For every $t \in \mathbb{N}^+$, by Theorem 4.2,

$$R_t^{\nu, \pi} = \sum_a \Delta_a^\nu \mathbb{E}^{\nu, \pi}(T_{t,a}^\pi) = \sum_a \Delta_a^\nu \sum_{k=1}^t \mathbb{E}^{\nu, \pi}(\mathbb{I}_{\{A_k=a\}}) = \sum_{k=1}^t \mathbb{E}^{\nu, \pi} \left(\sum_a \mathbb{I}_{\{A_k=a\}} \Delta_a^\nu \right) = \sum_{k=1}^t \mathbb{E}^{\nu, \pi}(\Delta_{A_k}^\nu).$$

Suppose that $\mathbb{P}^{\nu, \pi}(\mu_{A_k}^\nu = \mu_*^\nu) < 1$ for some $k \leq t$, so that $\mathbb{P}^{\nu, \pi}(\mu_{A_k}^\nu < \mu_*^\nu) > 0$ and $\mathbb{P}^{\nu, \pi}(\Delta_{A_k}^\nu > 0) > 0$. In that case, $\mathbb{E}^{\nu, \pi}(\Delta_{A_k}^\nu) > 0$, so that $R_t^{\nu, \pi} > 0$. \square

For convenience, let $R_0^{\nu, \pi} = 0$.

Proposition 4.9. If $R_t^{\nu, \pi} = o(t)$, then

$$\mu_*^\nu = \lim_{t \rightarrow \infty} \frac{1}{t} \sum_{k=1}^t \mathbb{E}^{\nu, \pi}(X_k).$$

Proof. Since $R_t^{\nu, \pi} : \mathbb{N} \rightarrow \mathbb{R}$ is asymptotically positive by assumption,

$$0 = \limsup_{t \rightarrow \infty} \frac{R_t^{\nu, \pi}}{t} \geq \liminf_{t \rightarrow \infty} \frac{R_t^{\nu, \pi}}{t} \geq 0,$$

so that

$$0 = \lim_{t \rightarrow \infty} \frac{R_t^{\nu, \pi}}{t} = \lim_{t \rightarrow \infty} \mu_*^\nu - \frac{1}{t} \sum_{k=1}^t \mathbb{E}^{\nu, \pi}(X_k) = \mu_*^\nu - \lim_{t \rightarrow \infty} \frac{1}{t} \sum_{k=1}^t \mathbb{E}^{\nu, \pi}(X_k).$$

\square

Definition 4.11. The number of times $T_{t,*}^{\nu, \pi} : \Omega \rightarrow \{0, \dots, t\}$ that policy π selects an optimal action on the stochastic bandit ν by time step $t \in \mathbb{N}^+$ is given by

$$T_{t,*}^{\nu, \pi}(\omega) = \sum_{k=1}^t \mathbb{I}_{\{\mu_{A_k}^\nu = \mu_*^\nu\}}(\omega) = \sum_{k=1}^t \mathbb{I}_{\{\Delta_{A_k}^\nu = 0\}}(\omega),$$

where $A_k = \pi_k(X_0, \dots, X_{k-1})$ for every $k \leq t$.

Proposition 4.10. The number of times $T_{t,*}^{\nu, \pi} : \Omega \rightarrow \{0, \dots, t\}$ that policy π selects an optimal action on the stochastic bandit ν by time step $t \in \mathbb{N}^+$ is given by

$$T_{t,*}^{\nu, \pi}(\omega) = \sum_{a | \Delta_a^\nu = 0} T_{t,a}^\pi(\omega).$$

Proof. For every $t \in \mathbb{N}^+$, let $A_k = \pi_k(X_0, \dots, X_{k-1})$ for every $k \leq t$. In that case,

$$\{\Delta_{A_k}^\nu = 0\} = \bigcup_a \{A_k = a \text{ and } \Delta_a^\nu = 0\} = \bigcup_{a|\Delta_a^\nu=0} \{A_k = a\},$$

so that

$$T_{t,*}^{\nu,\pi}(\omega) = \sum_{k=1}^t \mathbb{I}_{\{\Delta_{A_k}^\nu=0\}}(\omega) = \sum_{k=1}^t \sum_{a|\Delta_a^\nu=0} \mathbb{I}_{\{A_k=a\}}(\omega) = \sum_{a|\Delta_a^\nu=0} \sum_{k=1}^t \mathbb{I}_{\{A_k=a\}}(\omega) = \sum_{a|\Delta_a^\nu=0} T_{t,a}^\pi(\omega).$$

□

Proposition 4.11. If the set of actions \mathcal{A} is finite and $R_t^{\nu,\pi} = o(t)$, then

$$\lim_{t \rightarrow \infty} \frac{\mathbb{E}^{\nu,\pi}(T_{t,*}^{\nu,\pi})}{t} = 1.$$

Proof. By Theorem 4.2,

$$0 = \lim_{t \rightarrow \infty} \frac{R_t^{\nu,\pi}}{t} = \lim_{t \rightarrow \infty} \frac{\sum_a \Delta_a^\nu \mathbb{E}^{\nu,\pi}(T_{t,a}^\pi)}{t} = \lim_{t \rightarrow \infty} \sum_a \Delta_a^\nu \frac{\mathbb{E}^{\nu,\pi}(T_{t,a}^\pi)}{t} = \sum_a \Delta_a^\nu \lim_{t \rightarrow \infty} \frac{\mathbb{E}^{\nu,\pi}(T_{t,a}^\pi)}{t},$$

so that $\lim_{t \rightarrow \infty} \mathbb{E}^{\nu,\pi}(T_{t,a}^\pi)/t = 0$ whenever $\Delta_a^\nu > 0$. Therefore,

$$0 = \sum_{a|\Delta_a^\nu>0} \lim_{t \rightarrow \infty} \frac{\mathbb{E}^{\nu,\pi}(T_{t,a}^\pi)}{t} = \lim_{t \rightarrow \infty} \sum_{a|\Delta_a^\nu>0} \frac{\mathbb{E}^{\nu,\pi}(T_{t,a}^\pi)}{t}.$$

For every $t \in \mathbb{N}^+$, recall that $\sum_a T_{t,a}^\pi = t$. By Proposition 4.10,

$$t = \sum_a \mathbb{E}^{\nu,\pi}(T_{t,a}^\pi) = \sum_{a|\Delta_a^\nu=0} \mathbb{E}^{\nu,\pi}(T_{t,a}^\pi) + \sum_{a|\Delta_a^\nu>0} \mathbb{E}^{\nu,\pi}(T_{t,a}^\pi) = \mathbb{E}^{\nu,\pi}(T_{t,*}^{\nu,\pi}) + \sum_{a|\Delta_a^\nu>0} \mathbb{E}^{\nu,\pi}(T_{t,a}^\pi),$$

so that

$$\sum_{a|\Delta_a^\nu>0} \frac{\mathbb{E}^{\nu,\pi}(T_{t,a}^\pi)}{t} = 1 - \frac{\mathbb{E}^{\nu,\pi}(T_{t,*}^{\nu,\pi})}{t}.$$

Therefore, considering a previous equation,

$$0 = \lim_{t \rightarrow \infty} 1 - \frac{\mathbb{E}^{\nu,\pi}(T_{t,*}^{\nu,\pi})}{t} = 1 - \lim_{t \rightarrow \infty} \frac{\mathbb{E}^{\nu,\pi}(T_{t,*}^{\nu,\pi})}{t}.$$

Since $\mathbb{E}^{\nu,\pi}(T_{t,*}^{\nu,\pi}) > 0$ for some $t \in \mathbb{N}^+$ and $\mathbb{E}^{\nu,\pi}(T_{t,*}^{\nu,\pi}) \leq \mathbb{E}^{\nu,\pi}(T_{t,*}^{\nu,\pi})$, note that $\mathbb{E}^{\nu,\pi}(T_{t,*}^{\nu,\pi}) = \Theta(t)$. □

Definition 4.12. For a set of actions \mathcal{A} , an environment class \mathcal{E} is a set of stochastic bandits for \mathcal{A} .

Definition 4.13. For a set of actions \mathcal{A} and an environment class \mathcal{E} , consider a probability triple $(\mathcal{E}, \mathcal{G}, \mathbb{Q})$ such that $R_t^{\nu,\pi} : \mathcal{E} \rightarrow [0, \infty]$ is \mathcal{G} -measurable for every policy π and time step $t \in \mathbb{N}^+$. The Bayesian regret B_t^π of policy π after $t \in \mathbb{N}^+$ time steps is given by

$$B_t^\pi = \int_{\mathcal{E}} R_t^{\nu,\pi} Q(d\nu).$$

Definition 4.14. The stochastic bandit $\nu = (P_a \mid a \in \mathcal{A})$ is σ -subgaussian if, for every $a \in \mathcal{A}$, the random variable Z_a on the probability triple $(\mathbb{R}, \mathcal{B}(\mathbb{R}), P_a)$ given by $Z_a(x) = x - \mu_a^\nu$ is σ -subgaussian. Note that $\mathbb{E}_a(Z_a) = 0$.

5 Explore-then-commit

Definition 5.1. If $(x_n \in \mathbb{R} \mid n \in \mathbb{N})$ is a sequence of real numbers, then $\arg \max_n x_n$ is given by

$$\arg \max_n x_n = \inf(\{m \in \mathbb{N} \mid x_m = \sup_n x_n\}).$$

Note that $\arg \max_n x_n \in \mathbb{N} \cup \{\infty\}$, since $\inf(\emptyset) = \infty$.

Consider a measurable space (Ω, \mathcal{F}) and a stochastic process $(Y_n : \Omega \rightarrow \mathbb{R} \mid n \in \mathbb{N})$.

Definition 5.2. The function $\arg \max_n Y_n : \Omega \rightarrow \mathbb{N} \cup \{\infty\}$ is given by

$$\left(\arg \max_n Y_n \right) (\omega) = \arg \max_n Y_n(\omega).$$

Proposition 5.1. The function $\arg \max_n Y_n : \Omega \rightarrow \mathbb{N} \cup \{\infty\}$ is \mathcal{F} -measurable.

Proof. Recall that the function $\sup_n Y_n$ is \mathcal{F} -measurable, so that the function $Z_m : \Omega \rightarrow \mathbb{N} \cup \{\infty\}$ given by

$$Z_m(\omega) = m \mathbb{I}_{\{Y_m = \sup_n Y_n\}}(\omega) + \infty \mathbb{I}_{\{Y_m \neq \sup_n Y_n\}}(\omega) = \begin{cases} m, & \text{if } Y_m(\omega) = \sup_n Y_n(\omega), \\ \infty, & \text{if } Y_m(\omega) \neq \sup_n Y_n(\omega) \end{cases}$$

is \mathcal{F} -measurable for every $m \in \mathbb{N}$. Furthermore, recall that the function $\inf_m Z_m$ is \mathcal{F} -measurable and note that

$$\inf_m Z_m(\omega) = \inf \left(\left\{ m \in \mathbb{N} \mid Y_m(\omega) = \sup_n Y_n(\omega) \right\} \right) = \arg \max_n Y_n(\omega) = \left(\arg \max_n Y_n \right) (\omega).$$

□

Consider a number of actions $n \in \mathbb{N}^+$, a set of actions $\mathcal{A} = \{1, \dots, n\}$, a stochastic bandit $\nu = (P_a \mid a \in \mathcal{A})$, a policy $\pi = (\pi_t \mid t \in \mathbb{N}^+)$, and let $(\Omega, \mathcal{F}, \mathbb{P}^{\nu, \pi})$ be a canonical triple for the stochastic bandit ν under the policy π .

Definition 5.3. A policy π implements explore-then-commit with $m \in \mathbb{N}^+$ exploration steps if, for every $t \in \mathbb{N}^+$,

$$\pi_t(X_0, \dots, X_{t-1}) = \begin{cases} ((t-1) \bmod n) + 1, & \text{if } t \leq mn, \\ \arg \max_a M_{mn, a}^\pi, & \text{if } t > mn. \end{cases}$$

Note that $M_{t, a}^\pi$ is well-defined for every $t \geq n$ and $a \in \mathcal{A}$.

Proposition 5.2. If the policy π implements explore-then-commit with $m \in \mathbb{N}^+$ exploration steps and $t \leq mn$, then $\mathbb{P}^{\nu, \pi}(X_t \in B) = P_{a_t}(B)$ for every $B \in \mathcal{B}(\mathbb{R})$, where $a_t = ((t-1) \bmod n) + 1$.

Proof. For every $t \in \mathbb{N}^+$ such that $t \leq mn$, let $A_t = \pi_t(X_0, \dots, X_{t-1})$, so that $A_t = a_t$. For every $B \in \mathcal{B}(\mathbb{R})$,

$$\mathbb{P}^{\nu, \pi}(X_t \in B) = \mathbb{E}^{\nu, \pi}(\mathbb{E}^{\nu, \pi}(\mathbb{I}_{\{X_t \in B\}} \mid X_0, \dots, X_{t-1})) = \mathbb{E}^{\nu, \pi}(P_{A_t}(B)) = \mathbb{E}^{\nu, \pi}(P_{a_t}(B)) = P_{a_t}(B).$$

□

Proposition 5.3. If the policy π implements explore-then-commit with $m \in \mathbb{N}^+$ exploration steps, then the random variables X_0, X_1, \dots, X_{mn} are independent in $(\Omega, \mathcal{F}, \mathbb{P}^{\nu, \pi})$.

Proof. Note that X_0 and X_1 are independent because $\sigma(X_0) = \{\emptyset, \Omega\}$. Suppose that X_0, X_1, \dots, X_t are independent for some $t \in \mathbb{N}^+$ such that $t < mn$. We will show that X_0, X_1, \dots, X_{t+1} are independent.

For every $B_0, B_1, \dots, B_{t+1} \in \mathcal{B}(\mathbb{R})$, by taking out what is known,

$$\mathbb{P}^{\nu, \pi} \left(\bigcap_{k=0}^{t+1} \{X_k \in B_k\} \right) = \mathbb{E}^{\nu, \pi} \left(\prod_{k=0}^{t+1} \mathbb{I}_{\{X_k \in B_k\}} \right) = \mathbb{E}^{\nu, \pi} \left(\prod_{k=0}^t \mathbb{I}_{\{X_k \in B_k\}} \mathbb{E}^{\nu, \pi}(\mathbb{I}_{\{X_{t+1} \in B_{t+1}\}} \mid X_0, \dots, X_t) \right).$$

Let $a_{t+1} = (t \bmod n) + 1$, so that $\pi_{t+1}(X_0, \dots, X_t) = a_{t+1}$. In that case,

$$\mathbb{P}^{\nu, \pi} \left(\bigcap_{k=0}^{t+1} \{X_k \in B_k\} \right) = \mathbb{E}^{\nu, \pi} \left(\left(\prod_{k=0}^t \mathbb{I}_{\{X_k \in B_k\}} \right) P_{a_{t+1}}(B_{t+1}) \right) = \mathbb{E}^{\nu, \pi} \left(\prod_{k=0}^t \mathbb{I}_{\{X_k \in B_k\}} \right) P_{a_{t+1}}(B_{t+1}).$$

By Proposition 5.2 and because X_0, X_1, \dots, X_t are independent by assumption,

$$\mathbb{P}^{\nu, \pi} \left(\bigcap_{k=0}^{t+1} \{X_k \in B_k\} \right) = \mathbb{P}^{\nu, \pi} \left(\bigcap_{k=0}^t \{X_k \in B_k\} \right) \mathbb{P}^{\nu, \pi} (X_{t+1} \in B_{t+1}) = \prod_{k=0}^{t+1} \mathbb{P}^{\nu, \pi} (X_k \in B_k).$$

□

Proposition 5.4. If the policy π implements explore-then-commit with $m \in \mathbb{N}^+$ exploration steps and ν is a 1-subgaussian stochastic bandit, then $X_t - \mu_{a_t}^\nu$ is 1-subgaussian for every $t \leq mn$, where $a_t = ((t-1) \bmod n) + 1$.

Proof. For every $a \in \mathcal{A}$, recall that the random variable Z_a on the probability triple $(\mathbb{R}, \mathcal{B}(\mathbb{R}), P_a)$ is 1-subgaussian, where $Z_a(x) = x - \mu_a^\nu$. By Proposition 5.2, the law of X_t is P_{a_t} for every $t \in \{1, \dots, mn\}$. For every $\lambda \in \mathbb{R}$,

$$\mathbb{E}^{\nu, \pi} \left(e^{\lambda(X_t - \mu_{a_t}^\nu)} \right) = \int_{\mathbb{R}} e^{\lambda(x - \mu_{a_t}^\nu)} P_{a_t}(dx_t) = \int_{\mathbb{R}} e^{\lambda Z_{a_t}(x_t)} P_{a_t}(dx_t) = \mathbb{E}_{a_t} (e^{\lambda Z_{a_t}}) \leq e^{\frac{\lambda^2}{2}}.$$

□

Theorem 5.1. If the policy π implements explore-then-commit with $m \in \mathbb{N}^+$ exploration steps and ν is a 1-subgaussian stochastic bandit, for every $t \in \mathbb{N}^+$ such that $t \geq mn$,

$$R_t^{\nu, \pi} \leq \left(m \sum_{a=1}^n \Delta_a^\nu \right) + (t - mn) \sum_{a=1}^n \Delta_a^\nu e^{-\frac{m(\Delta_a^\nu)^2}{4}}.$$

Proof. For every $k \in \mathbb{N}^+$, let $A_k = \pi_k(X_0, \dots, X_{k-1})$. For every $a \in \mathcal{A}$,

$$T_{mn,a}^\pi(\omega) = \sum_{k=1}^{mn} \mathbb{I}_{\{A_k=a\}}(\omega) = \sum_{k=1}^{mn} \mathbb{I}_{\{((k-1) \bmod n)+1=a\}}(\omega) = m.$$

Theorem 4.2 completes the proof for the case where $t = mn$, since $(t - mn) = 0$ and

$$R_{mn}^{\nu, \pi} = \sum_{a=1}^n \Delta_a^\nu \mathbb{E}^{\nu, \pi} (T_{mn,a}^\pi) = m \sum_{a=1}^n \Delta_a^\nu.$$

Consider a time step $t \in \mathbb{N}^+$ such that $t > mn$. In that case,

$$T_{t,a}^\pi(\omega) = \sum_{k=1}^{mn} \mathbb{I}_{\{A_k=a\}}(\omega) + \sum_{k=mn+1}^t \mathbb{I}_{\{A_k=a\}}(\omega) = m + (t - mn) \mathbb{I}_{\{a = \arg \max_{a'} M_{mn,a'}^\pi\}}(\omega).$$

Because ties are possible, for every $a \in \mathcal{A}$ and $t > mn$,

$$\mathbb{E}^{\nu, \pi} (T_{t,a}^\pi) = m + (t - mn) \mathbb{P}^{\nu, \pi} \left(a = \arg \max_{a'} M_{mn,a'}^\pi \right) \leq m + (t - mn) \mathbb{P}^{\nu, \pi} \left(M_{mn,a}^\pi \geq \sup_{a'} M_{mn,a'}^\pi \right).$$

Let a^* denote an action such that $\mu_{a^*}^\nu = \mu_{*}^\nu$. For every $a \in \mathcal{A}$ and $t > mn$,

$$\mathbb{P}^{\nu, \pi} \left(M_{mn,a}^\pi \geq \sup_{a'} M_{mn,a'}^\pi \right) = \mathbb{P}^{\nu, \pi} \left(\bigcap_{a'} \{M_{mn,a}^\pi \geq M_{mn,a'}^\pi\} \right) \leq \mathbb{P}^{\nu, \pi} (M_{mn,a}^\pi \geq M_{mn,a^*}^\pi).$$

For every $a \in \mathcal{A}$ and $t > mn$, by adding Δ_a^ν to both sides of the inequality that defines an event,

$$\mathbb{P}^{\nu, \pi} \left(M_{mn,a}^\pi \geq \sup_{a'} M_{mn,a'}^\pi \right) \leq \mathbb{P}^{\nu, \pi} (M_{mn,a}^\pi - M_{mn,a^*}^\pi \geq 0) = \mathbb{P}^{\nu, \pi} (M_{mn,a}^\pi - M_{mn,a^*}^\pi + (\mu_{a^*}^\nu - \mu_a^\nu) \geq \Delta_a^\nu),$$

so that

$$\mathbb{P}^{\nu, \pi} \left(M_{mn,a}^\pi \geq \sup_{a'} M_{mn,a'}^\pi \right) \leq \mathbb{P}^{\nu, \pi} ((M_{mn,a}^\pi - \mu_a^\nu) - (M_{mn,a^*}^\pi - \mu_{a^*}^\nu) \geq \Delta_a^\nu).$$

For every $a \in \mathcal{A}$, by the definition of the average reward $M_{mn,a}^\pi$ that policy π observes for a by time mn ,

$$M_{mn,a}^\pi(\omega) - \mu_a^\nu = \left(\frac{1}{m} \sum_{i=0}^{m-1} X_{a+in}(\omega) \right) - \frac{1}{m} \sum_{i=0}^{m-1} \mu_a^\nu = \frac{1}{m} \sum_{i=0}^{m-1} (X_{a+in}(\omega) - \mu_a^\nu).$$

Proposition 5.4 guarantees that $X_{a+in} - \mu_a^\nu$ is 1-subgaussian for every $a \in \{1, \dots, n\}$ and $i \in \{0, \dots, m-1\}$, since $((a+in-1) \bmod n) + 1 = a$. Proposition 5.3 guarantees that $X_a, X_{a+n}, \dots, X_{a+(m-1)n}$ are independent. Therefore, $\sum_{i=0}^{m-1} (X_{a+in} - \mu_a^\nu)$ is \sqrt{m} -subgaussian, which implies that $M_{mn,a}^\pi - \mu_a^\nu$ is $1/\sqrt{m}$ -subgaussian. Since this applies for every $a \in \mathcal{A}$, we also conclude that $M_{mn,a^*}^\pi - \mu_{a^*}^\nu$ is $1/\sqrt{m}$ -subgaussian. For every $a \in \mathcal{A}$, note that $M_{mn,a}^\pi - \mu_a^\nu$ is $\sigma(X_a, X_{a+n}, \dots, X_{a+(m-1)n})$ -measurable. By Proposition 5.3, if $a \neq a^*$, then $(M_{mn,a}^\pi - \mu_a^\nu)$ and $-(M_{mn,a^*}^\pi - \mu_{a^*}^\nu)$ are independent, which further implies that $(M_{mn,a}^\pi - \mu_a^\nu) - (M_{mn,a^*}^\pi - \mu_{a^*}^\nu)$ is $\sqrt{2/m}$ -subgaussian. If $a = a^*$, then $(M_{mn,a}^\pi - \mu_a^\nu) - (M_{mn,a^*}^\pi - \mu_{a^*}^\nu) = 0$, and therefore also $\sqrt{2/m}$ -subgaussian. By Theorem 3.1, since $\Delta_a^\nu \geq 0$,

$$\mathbb{P}^{\nu, \pi} \left(M_{mn,a}^\pi \geq \sup_{a'} M_{mn,a'}^\pi \right) \leq e^{-\frac{(\Delta_a^\nu)^2}{2(\sqrt{2/m})^2}} = e^{-\frac{m(\Delta_a^\nu)^2}{4}}.$$

By returning to a previous inequality, for every $a \in \mathcal{A}$ and $t > mn$,

$$\mathbb{E}^{\nu, \pi}(T_{t,a}^\pi) \leq m + (t - mn)e^{-\frac{m(\Delta_a^\nu)^2}{4}}.$$

For every $t > mn$, Theorem 4.2 once again completes the proof, since

$$R_t^{\nu, \pi} = \sum_{a=1}^n \Delta_a^\nu \mathbb{E}^{\nu, \pi}(T_{t,a}^\pi) \leq \sum_{a=1}^n \Delta_a^\nu \left(m + (t - mn)e^{-\frac{m(\Delta_a^\nu)^2}{4}} \right) = \left(m \sum_{a=1}^n \Delta_a^\nu \right) + (t - mn) \sum_{a=1}^n \Delta_a^\nu e^{-\frac{m(\Delta_a^\nu)^2}{4}}.$$

□

In order to minimize the regret, the previous result suggests that the exploration factor m should balance between the first term (non-decreasing with respect to m) and the second term (non-increasing with respect to m). This is a specific instance of the so-called exploration-exploitation trade-off.

Proposition 5.5. Consider a 1-subgaussian stochastic bandit $\nu = (P_1, P_2)$. Let $\Delta = \max(\Delta_1^\nu, \Delta_2^\nu)$, and suppose that $\Delta > 0$. For some $t \in \mathbb{N}^+$, let $m = 1$ if $t \leq 4/\Delta^2$ and let $m = \left\lceil \frac{4}{\Delta^2} \log \left(\frac{t\Delta^2}{4} \right) \right\rceil$ if $t > 4/\Delta^2$. If π is a policy that implements explore-then-commit with m exploration steps, then

$$R_t^{\nu, \pi} \leq \Delta + \frac{4}{\sqrt{e}} \sqrt{t}.$$

Proof. First, consider some $t \in \mathbb{N}^+$ such that $t \leq 4/\Delta^2$, so that $m = 1$. By Theorem 4.2, since $\Delta \leq 2/\sqrt{t}$,

$$R_t^{\nu, \pi} = \sum_{a=1}^2 \Delta_a^\nu \mathbb{E}^{\nu, \pi}(T_{t,a}^\pi) \leq \Delta \sum_{a=1}^2 \mathbb{E}^{\nu, \pi}(T_{t,a}^\pi) = \Delta \mathbb{E}^{\nu, \pi} \left(\sum_{a=1}^2 T_{t,a}^\pi \right) = t\Delta \leq t \frac{2}{\sqrt{t}} = 2\sqrt{t}.$$

Second, consider some $t \in \mathbb{N}^+$ such that $t > 4/\Delta^2$, so that $m = \left\lceil \frac{4}{\Delta^2} \log \left(\frac{t\Delta^2}{4} \right) \right\rceil$. Note that $m \geq 1$ and

$$m\Delta = \Delta \left\lceil \frac{4}{\Delta^2} \log \left(\frac{t\Delta^2}{4} \right) \right\rceil \leq \Delta \left(1 + \frac{4}{\Delta^2} \log \left(\frac{t\Delta^2}{4} \right) \right) = \Delta + \frac{4}{\Delta} \log \left(\frac{t\Delta^2}{4} \right).$$

Consider the case where $t < 2m$. By Theorem 4.2,

$$R_t^{\nu, \pi} = \Delta_1^\nu \mathbb{E}^{\nu, \pi}(T_{t,1}^\pi) + \Delta_2^\nu \mathbb{E}^{\nu, \pi}(T_{t,2}^\pi) \leq m\Delta.$$

Now consider the case where $t \geq 2m$. By Theorem 5.1,

$$R_t^{\nu, \pi} \leq m\Delta + (t - 2m)\Delta e^{-\frac{m\Delta^2}{4}} \leq m\Delta + t\Delta e^{-\frac{m\Delta^2}{4}}.$$

Because the function $f : (0, \infty) \rightarrow (0, \infty)$ given by $f(x) = t\Delta e^{-\frac{x\Delta^2}{4}}$ is decreasing,

$$t\Delta e^{-\frac{m\Delta^2}{4}} = f(m) = f\left(\left\lceil \frac{4}{\Delta^2} \log\left(\frac{t\Delta^2}{4}\right) \right\rceil\right) \leq f\left(\frac{4}{\Delta^2} \log\left(\frac{t\Delta^2}{4}\right)\right) = t\Delta e^{-\log\left(\frac{t\Delta^2}{4}\right)} = \frac{4}{\Delta}.$$

Therefore, for every $t \in \mathbb{N}^+$ such that $t > 4/\Delta^2$,

$$R_t^{\nu, \pi} \leq m\Delta + t\Delta e^{-\frac{m\Delta^2}{4}} \leq \Delta + \frac{4}{\Delta} \log\left(\frac{t\Delta^2}{4}\right) + \frac{4}{\Delta}.$$

Consider the function $g : (0, \infty) \rightarrow \mathbb{R}$ given by $g(x) = x \log(4t/x^2) + x$, so that $g(4/\Delta) = (4/\Delta) \log(t\Delta^2/4) + 4/\Delta$. Note that $g(x) = x \log(4t) - 2x \log(x) + x$, $g'(x) = \log(4t) - 2 \log(x) - 1$, and $g''(x) = -2/x$. The second derivative test guarantees that $g(x) \leq g(2\sqrt{t}/\sqrt{e}) = 4\sqrt{t}/\sqrt{e}$ for every $x \in (0, \infty)$. Therefore, for every $t \in \mathbb{N}^+$,

$$R_t^{\nu, \pi} \leq \Delta + \frac{4}{\sqrt{e}} \sqrt{t}.$$

□

The previous result suggests a specific number of exploration steps for a policy that implements explore-then-commit. However, this policy is only suitable for a fixed horizon and a fixed suboptimality gap.

6 Restarts

Consider a number of actions $n \in \mathbb{N}^+$, a set of actions $\mathcal{A} = \{1, \dots, n\}$, a stochastic bandit $\nu = (P_a \mid a \in \mathcal{A})$, a policy $\pi = (\pi_t \mid t \in \mathbb{N}^+)$, and let $(\Omega, \mathcal{F}, \mathbb{P}^{\nu, \pi})$ be a canonical triple for the stochastic bandit ν under the policy π .

Definition 6.1. A policy π restarts to the policy π' after $t \in \mathbb{N}$ steps if, for all $k \in \mathbb{N}^+$ and $(x_0, \dots, x_{t+k-1}) \in \mathbb{R}^{t+k}$,

$$\pi_{t+k}(x_0, \dots, x_{t+k-1}) = \pi'_k(0, x_{t+1}, \dots, x_{t+k-1}).$$

Proposition 6.1. If a policy π restarts to the policy π' after $t \in \mathbb{N}$ steps, then

$$\mathbb{P}^{\nu, \pi}(X_{t+1} \in B_1, \dots, X_{t+k} \in B_k) = \mathbb{P}^{\nu, \pi'}(X_1 \in B_1, \dots, X_k \in B_k)$$

for every $k \in \mathbb{N}^+$ and $B_1, \dots, B_k \in \mathcal{B}(\mathbb{R})$.

Proof. Consider the case where $k = 1$. For every $B_1 \in \mathcal{B}(\mathbb{R})$,

$$\mathbb{P}^{\nu, \pi}(X_{t+1} \in B_1) = \mathbb{E}^{\nu, \pi}(\mathbb{E}^{\nu, \pi}(\mathbb{I}_{\{X_{t+1} \in B_1\}} \mid X_0, \dots, X_t)) = \mathbb{E}^{\nu, \pi}(P_{A_{t+1}}(B_1)),$$

where $A_{t+1} = \pi_{t+1}(X_0, \dots, X_t) = \pi'_1(0)$. Because A_{t+1} is a constant function,

$$\mathbb{P}^{\nu, \pi}(X_{t+1} \in B_1) = P_{\pi'_1(0)}(B_1) = \mathbb{E}^{\nu, \pi'}(P_{\pi'_1(0)}(B_1)) = \mathbb{E}^{\nu, \pi'}(P_{\pi'_1(X_0)}(B_1)) = \mathbb{P}^{\nu, \pi'}(X_1 \in B_1).$$

In order to employ induction, suppose that there is a $k \in \mathbb{N}^+$ such that, for every $B_1, \dots, B_k \in \mathcal{B}(\mathbb{R})$,

$$\mathbb{P}^{\nu, \pi}(X_{t+1} \in B_1, \dots, X_{t+k} \in B_k) = \mathbb{P}^{\nu, \pi'}(X_1 \in B_1, \dots, X_k \in B_k).$$

In that case, there is a probability measure $\mathcal{L} : \mathcal{B}(\mathbb{R}^k) \rightarrow [0, 1]$ on the measurable space $(\mathbb{R}^k, \mathcal{B}(\mathbb{R}^k))$ such that

$$\mathcal{L}(B_1 \times \dots \times B_k) = \mathbb{P}^{\nu, \pi}(X_{t+1} \in B_1, \dots, X_{t+k} \in B_k) = \mathbb{P}^{\nu, \pi'}(X_1 \in B_1, \dots, X_k \in B_k)$$

for every $B_1, \dots, B_k \in \mathcal{B}(\mathbb{R})$, so that \mathcal{L} is the joint law of $(X_{t+1}, \dots, X_{t+k})$ and the joint law of (X_1, \dots, X_k) .

For every $B_1, \dots, B_{k+1} \in \mathcal{B}(\mathbb{R})$,

$$\begin{aligned} \mathbb{P}^{\nu, \pi}(X_{t+1} \in B_1, \dots, X_{t+k+1} \in B_{k+1}) &= \mathbb{E}^{\nu, \pi}(\mathbb{E}^{\nu, \pi}(\mathbb{I}_{\{X_{t+1} \in B_1, \dots, X_{t+k} \in B_k\}} \mathbb{I}_{\{X_{t+k+1} \in B_{k+1}\}} \mid X_0, \dots, X_{t+k})), \\ \mathbb{P}^{\nu, \pi'}(X_1 \in B_1, \dots, X_{k+1} \in B_{k+1}) &= \mathbb{E}^{\nu, \pi'}(\mathbb{E}^{\nu, \pi'}(\mathbb{I}_{\{X_1 \in B_1, \dots, X_k \in B_k\}} \mathbb{I}_{\{X_{k+1} \in B_{k+1}\}} \mid X_0, \dots, X_k)). \end{aligned}$$

By taking out what is known,

$$\begin{aligned} \mathbb{P}^{\nu, \pi}(X_{t+1} \in B_1, \dots, X_{t+k+1} \in B_{k+1}) &= \mathbb{E}^{\nu, \pi}(\mathbb{I}_{\{X_{t+1} \in B_1, \dots, X_{t+k} \in B_k\}} P_{A_{t+k+1}}(B_{k+1})), \\ \mathbb{P}^{\nu, \pi'}(X_1 \in B_1, \dots, X_{k+1} \in B_{k+1}) &= \mathbb{E}^{\nu, \pi'}(\mathbb{I}_{\{X_1 \in B_1, \dots, X_k \in B_k\}} P_{A'_{k+1}}(B_{k+1})), \end{aligned}$$

where $A_{t+k+1} = \pi_{t+k+1}(X_0, \dots, X_{t+k})$ and $A'_{k+1} = \pi'_{k+1}(0, X_1, \dots, X_k)$. Since $A_{t+k+1} = \pi'_{k+1}(0, X_{t+1}, \dots, X_{t+k})$,

$$\begin{aligned} \mathbb{P}^{\nu, \pi}(X_{t+1} \in B_1, \dots, X_{t+k+1} \in B_{k+1}) &= \mathbb{E}^{\nu, \pi}(f(X_{t+1}, \dots, X_{t+k})), \\ \mathbb{P}^{\nu, \pi'}(X_1 \in B_1, \dots, X_{k+1} \in B_{k+1}) &= \mathbb{E}^{\nu, \pi'}(f(X_1, \dots, X_k)), \end{aligned}$$

where the function $f : \mathbb{R}^k \rightarrow [0, 1]$ is given by

$$f(x) = \left(\prod_{i=1}^k \mathbb{I}_{B_i}(x_i) \right) P_{\pi'_{k+1}(0, x_1, \dots, x_k)}(B_{k+1}).$$

Since \mathcal{L} is the joint law of $(X_{t+1}, \dots, X_{t+k})$ and the joint law of (X_1, \dots, X_k) ,

$$\mathbb{P}^{\nu, \pi}(X_{t+1} \in B_1, \dots, X_{t+k+1} \in B_{k+1}) = \int_{\mathbb{R}^k} f(x) \mathcal{L}(dx) = \mathbb{P}^{\nu, \pi'}(X_1 \in B_1, \dots, X_{k+1} \in B_{k+1}).$$

□

Proposition 6.2. If a policy π restarts to the policy π' after $t \in \mathbb{N}^+$ steps, for every $h \in \mathbb{N}^+$,

$$R_{t+h}^{\nu, \pi} = R_t^{\nu, \pi} + R_h^{\nu, \pi'}.$$

Proof. For every $h \in \mathbb{N}^+$, by definition of the regret $R_{t+h}^{\nu, \pi}$,

$$R_{t+h}^{\nu, \pi} = (t+h)\mu_*^\nu - \sum_{k=1}^{t+h} \mathbb{E}^{\nu, \pi}(X_k) = \left(t\mu_*^\nu - \sum_{k=1}^t \mathbb{E}^{\nu, \pi}(X_k) \right) + \left(h\mu_*^\nu - \sum_{k=t+1}^{t+h} \mathbb{E}^{\nu, \pi}(X_k) \right).$$

By definition of the regret $R_t^{\nu, \pi}$ and changing the indices of the second summation,

$$R_{t+h}^{\nu, \pi} = R_t^{\nu, \pi} + \left(h\mu_*^\nu - \sum_{k=1}^h \mathbb{E}^{\nu, \pi}(X_{t+k}) \right).$$

By Proposition 6.1, we know that $\mathbb{P}^{\nu, \pi}(X_{t+k} \in B) = \mathbb{P}^{\nu, \pi'}(X_k \in B)$ for every $k \in \mathbb{N}^+$ and $B \in \mathcal{B}(\mathbb{R})$. Therefore, $\mathbb{E}^{\nu, \pi}(X_{t+k}) = \mathbb{E}^{\nu, \pi'}(X_k)$ for every $k \in \mathbb{N}^+$ and

$$R_{t+h}^{\nu, \pi} = R_t^{\nu, \pi} + \left(h\mu_*^\nu - \sum_{k=1}^h \mathbb{E}^{\nu, \pi'}(X_k) \right) = R_t^{\nu, \pi} + R_h^{\nu, \pi'}.$$

□

Definition 6.2. Consider a sequence of policies $(\pi^{(k)} \mid k \in \mathbb{N}^+)$ and a sequence of positive natural numbers $(h_k \in \mathbb{N}^+ \mid k \in \mathbb{N}^+)$. For every $k \in \mathbb{N}^+$, suppose that the policy $\pi^{(k)}$ restarts to the policy $\pi^{(k+1)}$ after h_k steps. If $\pi = \pi^{(1)}$, we say that policy π restarts to the sequence of policies $(\pi^{(k)} \mid k \in \mathbb{N}^+)$ given the sequence of relative steps $(h_k \mid k \in \mathbb{N}^+)$.

Proposition 6.3. If the policy π restarts to the sequence of policies $(\pi^{(k)} \mid k \in \mathbb{N}^+)$ given the sequence of relative steps $(h_k \in \mathbb{N}^+ \mid k \in \mathbb{N}^+)$, for every $l \in \mathbb{N}^+$,

$$R_{\sum_{k=1}^l h_k}^{\nu, \pi} = \sum_{k=1}^l R_{h_k}^{\nu, \pi^{(k)}}.$$

Proof. If $l = 1$, then $R_{h_1}^{\nu, \pi} = R_{h_1}^{\nu, \pi^{(1)}}$. By Proposition 6.2, if $l > 1$, then

$$R_{\sum_{k=1}^l h_k}^{\nu, \pi} = R_{\sum_{k=1}^l h_k}^{\nu, \pi^{(1)}} = R_{h_1}^{\nu, \pi^{(1)}} + R_{\sum_{k=2}^l h_k}^{\nu, \pi^{(2)}} = \dots = \sum_{k=1}^l R_{h_k}^{\nu, \pi^{(k)}}.$$

□

Proposition 6.4. If the policy π restarts to the sequence of policies $(\pi^{(k)} \mid k \in \mathbb{N}^+)$ given the sequence of relative steps $(h_k \in \mathbb{N}^+ \mid k \in \mathbb{N}^+)$ and there is a function $f : \mathbb{N}^+ \rightarrow [0, \infty)$ such that $R_{h_k}^{\nu, \pi^{(k)}} \leq f(h_k)$ for every $k \in \mathbb{N}^+$, then

$$R_t^{\nu, \pi} \leq \sum_{k=1}^{p_t} f(h_k)$$

for every $t \in \mathbb{N}^+$, where $p_t = \min\{l \in \mathbb{N}^+ \mid \sum_{k=1}^l h_k \geq t\}$ is the number of restarts by time step t .

Proof. For every $t \in \mathbb{N}^+$, let $p_t = \min\{l \in \mathbb{N}^+ \mid \sum_{k=1}^l h_k \geq t\}$, so that $\sum_{k=1}^{p_t} h_k \geq t$. By Proposition 6.3,

$$R_t^{\nu, \pi} \leq R_{\sum_{k=1}^{p_t} h_k}^{\nu, \pi} = \sum_{k=1}^{p_t} R_{h_k}^{\nu, \pi^{(k)}} \leq \sum_{k=1}^{p_t} f(h_k).$$

□

The previous result can be used to provide a regret upper bound based on the regret upper bounds of policies suitable for fixed horizons. This is exemplified by the so-called doubling trick, which is presented below.

Proposition 6.5. If the policy π restarts to the sequence of policies $(\pi^{(k)} \mid k \in \mathbb{N}^+)$ given the sequence of relative steps $(2^{k-1} \mid k \in \mathbb{N}^+)$ and $R_{2^{k-1}}^{\nu, \pi^{(k)}} \leq \sqrt{2^{k-1}}$ for every $k \in \mathbb{N}^+$, then, for every $t \in \mathbb{N}^+$,

$$R_t^{\nu, \pi} \leq 2(1 + \sqrt{2})\sqrt{t}.$$

Proof. For every $t \in \mathbb{N}^+$, let $p_t = \min\{l \in \mathbb{N}^+ \mid \sum_{k=1}^l 2^{k-1} \geq t\}$, so that $p_t = \lceil \log_2(t+1) \rceil$. By Proposition 6.4,

$$R_t^{\nu, \pi} \leq \sum_{k=1}^{p_t} \sqrt{2^{k-1}} = \sum_{k=1}^{p_t} (\sqrt{2})^{k-1} = \frac{(\sqrt{2})^{p_t} - 1}{\sqrt{2} - 1} \leq \frac{(\sqrt{2})^{p_t}}{\sqrt{2} - 1}.$$

Since $p_t \leq \log_2(t+1) + 1 = \log_2(t+1) + \log_2(2) = \log_2 2(t+1)$ and $1 + 1/t \leq 2$,

$$R_t^{\nu, \pi} \leq \frac{(\sqrt{2})^{\log_2 2(t+1)}}{\sqrt{2} - 1} = \frac{\sqrt{2(t+1)}}{\sqrt{2} - 1} = \frac{1}{\sqrt{2} - 1} \sqrt{2t \left(1 + \frac{1}{t}\right)} \leq \frac{\sqrt{4t}}{\sqrt{2} - 1} = \frac{2\sqrt{t}}{\sqrt{2} - 1}.$$

□

Note that doubling the horizon after each restart is not generally appropriate.

7 Action times

Consider a number of actions $n \in \mathbb{N}^+$, a set of actions $\mathcal{A} = \{1, \dots, n\}$, a stochastic bandit $\nu = (P_a \mid a \in \mathcal{A})$, a policy $\pi = (\pi_t \mid t \in \mathbb{N}^+)$, and a canonical triple $(\Omega, \mathcal{F}, \mathbb{P}^{\nu, \pi})$ for the stochastic bandit ν under the policy π . Furthermore, let $(\mathcal{F}_t)_t$ denote the natural filtration of the reward process $(X_t \mid t \in \mathbb{N})$, so that $\mathcal{F}_t = \sigma(X_0, \dots, X_t)$ for every $t \in \mathbb{N}$.

Definition 7.1. The time $C_{m,a}^\pi : \Omega \rightarrow \mathbb{N}^+ \cup \{\infty\}$ until policy π selects $a \in \mathcal{A}$ exactly $m \in \mathbb{N}^+$ times is given by

$$C_{m,a}^\pi(\omega) = \inf \left(\{t \in \mathbb{N}^+ \mid T_{t,a}^\pi(\omega) \geq m\} \right).$$

If $t \in \mathbb{N}^+$ and $C_{m,a}^\pi(\omega) = t$, then $\pi_t(X_0(\omega), \dots, X_{t-1}(\omega)) = a$ and $C_{m+1,a}^\pi(\omega) > t$.

Proposition 7.1. The time $C_{m,a}^\pi : \Omega \rightarrow \mathbb{N}^+ \cup \{\infty\}$ until π selects $a \in \mathcal{A}$ exactly $m \in \mathbb{N}^+$ times is a stopping time.

Proof. Recall that $C_{m,a}^\pi$ is a stopping time if $\{C_{m,a}^\pi \leq t\} \in \mathcal{F}_t$ for every $t \in \mathbb{N} \cup \{\infty\}$. If $t = 0$, then $\{C_{m,a}^\pi \leq 0\} = \emptyset$. If $t \in \mathbb{N}^+$, then $\{C_{m,a}^\pi \leq t\} = \{T_{t,a}^\pi \geq m\}$ and $\{T_{t,a}^\pi \geq m\} \in \mathcal{F}_{t-1}$. If $t = \infty$, then $\{C_{m,a}^\pi \leq \infty\} = \Omega$. \square

Definition 7.2. For every $a \in \mathcal{A}$ and $m \in \mathbb{N}^+$, the function $X_{C_{m,a}^\pi} : \Omega \rightarrow \mathbb{R}$ is given by

$$X_{C_{m,a}^\pi}(\omega) = \begin{cases} X_{C_{m,a}^\pi(\omega)}(\omega), & \text{if } C_{m,a}^\pi(\omega) < \infty, \\ 0, & \text{if } C_{m,a}^\pi(\omega) = \infty. \end{cases}$$

Recall that $X_{C_{m,a}^\pi}$ is \mathcal{F} -measurable because $(X_t \mid t \in \mathbb{N})$ is adapted to $(\mathcal{F}_t)_t$ and $C_{m,a}^\pi$ is a stopping time.

Definition 7.3. For every $a \in \mathcal{A}$, the constant policy $\pi^{(a)} = (\pi_t^{(a)} \mid t \in \mathbb{N}^+)$ is given by $\pi_t^{(a)} = a$ for every $t \in \mathbb{N}^+$.

Proposition 7.2. For every $a \in \mathcal{A}$, $m \in \mathbb{N}^+$, and $B_1, \dots, B_m \in \mathcal{B}(\mathbb{R})$,

$$\mathbb{P}^{\nu, \pi^{(a)}}(X_1 \in B_1, \dots, X_m \in B_m) = \prod_{k=1}^m P_a(B_k).$$

Proof. For every $a \in \mathcal{A}$, $m \in \mathbb{N}^+$, and $B_1, \dots, B_m \in \mathcal{B}(\mathbb{R})$, if the empty product denotes one,

$$\mathbb{P}^{\nu, \pi^{(a)}}(X_1 \in B_1, \dots, X_m \in B_m) = \mathbb{E}^{\nu, \pi^{(a)}} \left(\mathbb{E}^{\nu, \pi^{(a)}} \left(\left(\prod_{k=1}^{m-1} \mathbb{I}_{\{X_k \in B_k\}} \right) \mathbb{I}_{\{X_m \in B_m\}} \mid X_0, \dots, X_{m-1} \right) \right).$$

By taking out what is known and using the fact that $\pi_m^{(a)}(X_0, \dots, X_{m-1}) = a$,

$$\mathbb{P}^{\nu, \pi^{(a)}}(X_1 \in B_1, \dots, X_m \in B_m) = P_a(B_m) \mathbb{E}^{\nu, \pi^{(a)}} \left(\prod_{k=1}^{m-1} \mathbb{I}_{\{X_k \in B_k\}} \right).$$

Therefore, $\mathbb{P}^{\nu, \pi^{(a)}}(X_1 \in B_1) = P_a(B_1)$. Suppose that the proposition is true for some $m-1 \in \mathbb{N}^+$. In that case,

$$\mathbb{P}^{\nu, \pi^{(a)}}(X_1 \in B_1, \dots, X_m \in B_m) = P_a(B_m) \mathbb{P}^{\nu, \pi^{(a)}}(X_1 \in B_1, \dots, X_{m-1} \in B_{m-1}) = \prod_{k=1}^m P_a(B_k).$$

\square

Proposition 7.3. For every $a \in \mathcal{A}$, $m \in \mathbb{N}^+$, and $t \in \mathbb{N}^+$, if $h : \mathbb{R} \rightarrow \mathbb{R}$ is $\mathcal{B}(\mathbb{R})$ -measurable, then the function $\mathbb{I}_{\{C_{m,a}^\pi = t\}} \prod_{k=1}^{m-1} h(X_{C_{k,a}^\pi})$ is \mathcal{F}_{t-1} -measurable.

Proof. For every $a \in \mathcal{A}$, $k \in \mathbb{N}^+$, and $t_k \in \mathbb{N}^+$, note that $\{C_{k,a}^\pi = t_k\} = \{C_{k,a}^\pi \leq t_k\} \cap \{C_{k,a}^\pi \leq t_k - 1\}^c$, so that $\{C_{k,a}^\pi = t_k\} \in \mathcal{F}_{t_k-1}$. For every $\omega \in \Omega$, $m \in \mathbb{N}^+$, and $t \in \mathbb{N}^+$, if $C_{m,a}^\pi(\omega) = t$, then $C_{1,a}^\pi(\omega) < \dots < C_{m,a}^\pi(\omega) = t$, so

$$\mathbb{I}_{\{C_{m,a}^\pi = t\}} \prod_{k=1}^{m-1} h(X_{C_{k,a}^\pi}) = \mathbb{I}_{\{C_{m,a}^\pi = t\}} \left(\prod_{k=1}^{m-1} \sum_{t_k < t} \mathbb{I}_{\{C_{k,a}^\pi = t_k\}} h(X_{t_k}) \right).$$

If $k \in \mathbb{N}^+$ and $t_k \leq t$, then $\mathbb{I}_{\{C_{k,a}^\pi = t_k\}}$ is \mathcal{F}_{t-1} -measurable. If $t_k < t$, then $h(X_{t_k})$ is also \mathcal{F}_{t-1} -measurable. \square

Proposition 7.4. For every $a \in \mathcal{A}$ and $m \in \mathbb{N}^+$, if a function $h : \mathbb{R} \rightarrow [0, \infty]$ is ν -integrable, then

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi < \infty\}} \prod_{k=1}^m h(X_{C_{k,a}^\pi}) \right) \leq \mathbb{E}^{\nu, \pi^{(a)}} \left(\prod_{k=1}^m h(X_k) \right)$$

whenever $\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi = t\}} \prod_{k=1}^m h(X_{C_{k,a}^\pi}) \right) < \infty$ for every $t \in \mathbb{N}^+$.

Proof. For every $a \in \mathcal{A}$ and $t \in \mathbb{N}^+$, if h is ν -integrable, then $\mathbb{E}^{\nu, \pi^{(a)}}(h(X_t)) < \infty$. Therefore, for every $m \in \mathbb{N}^+$,

$$\mathbb{E}^{\nu, \pi^{(a)}} \left(\prod_{k=1}^m h(X_k) \right) = \prod_{k=1}^m \mathbb{E}^{\nu, \pi^{(a)}}(h(X_k)) = \prod_{k=1}^m \int_{\mathbb{R}} h(x) P_a(dx) = \left(\int_{\mathbb{R}} h(x) P_a(dx) \right)^m,$$

which uses the fact that X_1, \dots, X_m are independent and identically distributed with respect to $\mathbb{P}^{\nu, \pi^{(a)}}$.

For every $a \in \mathcal{A}$ and $m \in \mathbb{N}^+$, if the empty product denotes one,

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi < \infty\}} \prod_{k=1}^m h(X_{C_{k,a}^\pi}) \right) = \sum_{t \in \mathbb{N}^+} \mathbb{E}^{\nu, \pi} \left(\left(\mathbb{I}_{\{C_{m,a}^\pi = t\}} \prod_{k=1}^{m-1} h(X_{C_{k,a}^\pi}) \right) h(X_t) \right).$$

Since each expectation on the right side above is finite by assumption, by taking out what is known,

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi < \infty\}} \prod_{k=1}^m h(X_{C_{k,a}^\pi}) \right) = \sum_{t \in \mathbb{N}^+} \mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi = t\}} \prod_{k=1}^{m-1} h(X_{C_{k,a}^\pi}) \mathbb{E}^{\nu, \pi}(h(X_t) \mid X_0, \dots, X_{t-1}) \right).$$

By Proposition 4.3, if $A_t = \pi_t(X_0, \dots, X_{t-1})$, then almost surely

$$\mathbb{E}^{\nu, \pi}(h(X_t) \mid X_0, \dots, X_{t-1}) = \sum_{a'} \mathbb{I}_{\{A_t = a'\}} \int_{\mathbb{R}} h(x) P_{a'}(dx).$$

For every $\omega \in \Omega$, recall that $C_{m,a}^\pi(\omega) = t$ implies $A_t(\omega) = a$. Therefore, almost surely,

$$\mathbb{I}_{\{C_{m,a}^\pi = t\}} \mathbb{E}^{\nu, \pi}(h(X_t) \mid X_0, \dots, X_{t-1}) = \mathbb{I}_{\{C_{m,a}^\pi = t\}} \int_{\mathbb{R}} h(x) P_a(dx).$$

By returning to a previous equation,

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi < \infty\}} \prod_{k=1}^m h(X_{C_{k,a}^\pi}) \right) = \left(\int_{\mathbb{R}} h(x) P_a(dx) \right) \mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi < \infty\}} \prod_{k=1}^{m-1} h(X_{C_{k,a}^\pi}) \right).$$

The proposition is true for $m = 1$, since

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{1,a}^\pi < \infty\}} h(X_{C_{1,a}^\pi}) \right) = \left(\int_{\mathbb{R}} h(x) P_a(dx) \right) \mathbb{P}^{\nu, \pi}(C_{1,a}^\pi < \infty) \leq \int_{\mathbb{R}} h(x) P_a(dx).$$

If the proposition is true for some $m - 1 \in \mathbb{N}^+$, because $C_{m,a}^\pi(\omega) < \infty$ implies $C_{m-1,a}^\pi(\omega) < \infty$ for every $\omega \in \Omega$,

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi < \infty\}} \prod_{k=1}^m h(X_{C_{k,a}^\pi}) \right) \leq \left(\int_{\mathbb{R}} h(x) P_a(dx) \right) \mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m-1,a}^\pi < \infty\}} \prod_{k=1}^{m-1} h(X_{C_{k,a}^\pi}) \right) \leq \left(\int_{\mathbb{R}} h(x) P_a(dx) \right)^m.$$

□

Proposition 7.5. If ν is a 1-subgaussian stochastic bandit and $\lambda \in \mathbb{R}$, then the function $h : \mathbb{R} \rightarrow [0, \infty]$ given by $h(x) = e^{\lambda x}$ is ν -integrable. Furthermore, for every $a \in \mathcal{A}$, $m \in \mathbb{N}^+$, and $t \in \mathbb{N}^+$,

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi = t\}} \prod_{k=1}^m h(X_{C_{k,a}^\pi}) \right) < \infty.$$

Proof. If ν is a 1-subgaussian stochastic bandit, recall that the random variable Z_a on the probability triple $(\mathbb{R}, \mathcal{B}(\mathbb{R}), P_a)$ given by $Z_a(x) = x - \mu_a^\nu$ is 1-subgaussian for every $a \in \mathcal{A}$. For every $\lambda \in \mathbb{R}$,

$$\int_{\mathbb{R}} e^{\lambda x} P_a(dx) = \int_{\mathbb{R}} e^{\lambda(Z_a(x) + \mu_a^\nu)} P_a(dx) = e^{\lambda \mu_a^\nu} \int_{\mathbb{R}} e^{\lambda Z_a(x)} P_a(dx) \leq e^{\lambda \mu_a^\nu} e^{\frac{\lambda^2}{2}}.$$

By Proposition 4.1, there is a constant $c \in [0, \infty)$ such that $\mu_a^\nu \in [-c, c]$ for every $a \in \mathcal{A}$. Therefore, the function $h : \mathbb{R} \rightarrow [0, \infty]$ given by $h(x) = e^{\lambda x}$ is ν -integrable.

Let $a \in \mathcal{A}$ and $t \in \mathbb{N}^+$. We will use induction to show that, for every $m \in \mathbb{N}^+$ and $\lambda \in \mathbb{R}$,

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi \leq t\}} e^{\lambda \sum_{k=1}^m X_{C_{k,a}^\pi}} \right) < \infty.$$

Consider the case where $m = 1$. For every $\lambda \in \mathbb{R}$, since $\mathbb{E}^{\nu, \pi}(e^{\lambda X_{t'}}) < \infty$ for every $t' \in \mathbb{N}^+$,

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{1,a}^\pi \leq t\}} e^{\lambda X_{C_{1,a}^\pi}} \right) = \sum_{t' \leq t} \mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{1,a}^\pi = t'\}} e^{\lambda X_{t'}} \right) \leq \sum_{t' \leq t} \mathbb{E}^{\nu, \pi} (e^{\lambda X_{t'}}) < \infty.$$

Suppose that there is an $m-1 \in \mathbb{N}^+$ such that, for every $\lambda' \in \mathbb{R}$,

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m-1,a}^\pi \leq t\}} e^{\lambda' \sum_{k=1}^{m-1} X_{C_{k,a}^\pi}} \right) < \infty.$$

For every $\lambda \in \mathbb{R}$, since $\mathbb{I}_{\{C_{m,a}^\pi \leq t\}} = \mathbb{I}_{\{C_{m-1,a}^\pi \leq t\}} \mathbb{I}_{\{C_{m,a}^\pi \leq t\}}$,

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi \leq t\}} e^{\lambda \sum_{k=1}^m X_{C_{k,a}^\pi}} \right) = \mathbb{E}^{\nu, \pi} \left(\left(\mathbb{I}_{\{C_{m-1,a}^\pi \leq t\}} e^{\lambda \sum_{k=1}^{m-1} X_{C_{k,a}^\pi}} \right) \left(\mathbb{I}_{\{C_{m,a}^\pi \leq t\}} e^{\lambda X_{C_{m,a}^\pi}} \right) \right).$$

If $\lambda' = 2\lambda$, by the inductive hypothesis,

$$\mathbb{E}^{\nu, \pi} \left(\left(\mathbb{I}_{\{C_{m-1,a}^\pi \leq t\}} e^{\lambda \sum_{k=1}^{m-1} X_{C_{k,a}^\pi}} \right)^2 \right) = \mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m-1,a}^\pi \leq t\}} e^{\lambda' \sum_{k=1}^{m-1} X_{C_{k,a}^\pi}} \right) < \infty.$$

Since $\mathbb{E}^{\nu, \pi}(e^{\lambda' X_{t'}}) < \infty$ for every $t' \in \mathbb{N}^+$,

$$\mathbb{E}^{\nu, \pi} \left(\left(\mathbb{I}_{\{C_{m,a}^\pi \leq t\}} e^{\lambda X_{C_{m,a}^\pi}} \right)^2 \right) = \mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi \leq t\}} e^{\lambda' X_{C_{m,a}^\pi}} \right) = \sum_{t' \leq t} \mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi = t'\}} e^{\lambda' X_{t'}} \right) \leq \sum_{t' \leq t} \mathbb{E}^{\nu, \pi} (e^{\lambda' X_{t'}}) < \infty.$$

By the Schwarz inequality, for every $\lambda \in \mathbb{R}$,

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi \leq t\}} e^{\lambda \sum_{k=1}^m X_{C_{k,a}^\pi}} \right) < \infty.$$

Therefore, for every $a \in \mathcal{A}$, $m \in \mathbb{N}^+$, $t \in \mathbb{N}^+$, and $\lambda \in \mathbb{R}$, if $h : \mathbb{R} \rightarrow [0, \infty]$ is given by $h(x) = e^{\lambda x}$,

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi = t\}} \prod_{k=1}^m h(X_{C_{k,a}^\pi}) \right) \leq \mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi \leq t\}} \prod_{k=1}^m h(X_{C_{k,a}^\pi}) \right) = \mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi \leq t\}} e^{\lambda \sum_{k=1}^m X_{C_{k,a}^\pi}} \right) < \infty.$$

□

Proposition 7.6. If ν is a 1-subgaussian stochastic bandit, then, for every $a \in \mathcal{A}$, $m \in \mathbb{N}^+$, and $\lambda \in \mathbb{R}$,

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi < \infty\}} e^{\frac{\lambda}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu)} \right) \leq e^{\frac{\lambda^2}{2m}}.$$

Proof. For some $m \in \mathbb{N}^+$ and $\lambda \in \mathbb{R}$, consider the function $h : \mathbb{R} \rightarrow [0, \infty]$ given by $h(x) = e^{\frac{\lambda}{m} x}$, which is ν -integrable by Proposition 7.5. Recall that, for every $a \in \mathcal{A}$ and $t \in \mathbb{N}^+$,

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi = t\}} \prod_{k=1}^m h(X_{C_{k,a}^\pi}) \right) < \infty.$$

For every $a \in \mathcal{A}$, consider the function $h_a : \mathbb{R} \rightarrow [0, \infty]$ given by $h_a(x) = e^{\frac{\lambda}{m}(x - \mu_a^\nu)} = h(x)e^{-\frac{\lambda}{m}\mu_a^\nu}$. Since h is ν -integrable, h_a is also ν -integrable. Furthermore, for every $t \in \mathbb{N}^+$,

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi = t\}} \prod_{k=1}^m h_a(X_{C_{k,a}^\pi}) \right) = \mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi = t\}} \prod_{k=1}^m h(X_{C_{k,a}^\pi}) \right) e^{-\lambda \mu_a^\nu} < \infty.$$

By Proposition 7.4,

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi < \infty\}} \prod_{k=1}^m h_a(X_{C_{k,a}^\pi}) \right) \leq \mathbb{E}^{\nu, \pi^{(a)}} \left(\prod_{k=1}^m h_a(X_k) \right).$$

By rewriting the previous inequality, for every $a \in \mathcal{A}$, $m \in \mathbb{N}^+$, and $\lambda \in \mathbb{R}$,

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi < \infty\}} e^{\frac{\lambda}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu)} \right) \leq \mathbb{E}^{\nu, \pi^{(a)}} \left(e^{\frac{\lambda}{m} \sum_{k=1}^m (X_k - \mu_a^\nu)} \right).$$

Since $X_1 - \mu_a^\nu, \dots, X_m - \mu_a^\nu$ are independent 1-subgaussian random variables with respect to $\mathbb{P}^{\nu, \pi^{(a)}}$, the random variable $\sum_{k=1}^m (X_k - \mu_a^\nu)$ is \sqrt{m} -subgaussian, which implies that $(1/m) \sum_{k=1}^m (X_k - \mu_a^\nu)$ is $1/\sqrt{m}$ -subgaussian. Therefore, by the definition of a $1/\sqrt{m}$ -subgaussian random variable,

$$\mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi < \infty\}} e^{\frac{\lambda}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu)} \right) \leq \mathbb{E}^{\nu, \pi^{(a)}} \left(e^{\lambda \frac{1}{m} \sum_{k=1}^m (X_k - \mu_a^\nu)} \right) \leq e^{\frac{\lambda^2}{2m}}.$$

□

Proposition 7.7. If ν is a 1-subgaussian stochastic bandit, then, for every $a \in \mathcal{A}$, $m \in \mathbb{N}^+$, and $\epsilon \geq 0$,

$$\begin{aligned} \mathbb{P}^{\nu, \pi} \left(C_{m,a}^\pi < \infty, \frac{1}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu) \leq -\epsilon \right) &\leq e^{-\frac{m\epsilon^2}{2}}, \\ \mathbb{P}^{\nu, \pi} \left(C_{m,a}^\pi < \infty, \frac{1}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu) \geq \epsilon \right) &\leq e^{-\frac{m\epsilon^2}{2}}. \end{aligned}$$

Proof. For every $a \in \mathcal{A}$, $m \in \mathbb{N}^+$, $\epsilon \in \mathbb{R}$, and $\lambda \geq 0$,

$$\begin{aligned} \mathbb{I}_{\{C_{m,a}^\pi < \infty\}} e^{-\frac{\lambda}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu)} &\geq \mathbb{I}_{\{C_{m,a}^\pi < \infty\}} e^{-\frac{\lambda}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu)} \mathbb{I}_{\{-\frac{1}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu) \geq \epsilon\}}, \\ \mathbb{I}_{\{C_{m,a}^\pi < \infty\}} e^{\frac{\lambda}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu)} &\geq \mathbb{I}_{\{C_{m,a}^\pi < \infty\}} e^{\frac{\lambda}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu)} \mathbb{I}_{\{\frac{1}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu) \geq \epsilon\}}. \end{aligned}$$

Since the function $g : \mathbb{R} \rightarrow [0, \infty]$ given by $g(x) = e^{\lambda x}$ is non-decreasing for $\lambda \geq 0$,

$$\begin{aligned} \mathbb{I}_{\{C_{m,a}^\pi < \infty\}} e^{-\frac{\lambda}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu)} &\geq \mathbb{I}_{\{C_{m,a}^\pi < \infty\}} e^{\lambda \epsilon} \mathbb{I}_{\{-\frac{1}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu) \geq \epsilon\}}, \\ \mathbb{I}_{\{C_{m,a}^\pi < \infty\}} e^{\frac{\lambda}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu)} &\geq \mathbb{I}_{\{C_{m,a}^\pi < \infty\}} e^{\lambda \epsilon} \mathbb{I}_{\{\frac{1}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu) \geq \epsilon\}}. \end{aligned}$$

By taking expectations of both sides of the inequalities above,

$$\begin{aligned} \mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi < \infty\}} e^{-\frac{\lambda}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu)} \right) &\geq e^{\lambda \epsilon} \mathbb{P}^{\nu, \pi} \left(C_{m,a}^\pi < \infty, -\frac{1}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu) \geq \epsilon \right), \\ \mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi < \infty\}} e^{\frac{\lambda}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu)} \right) &\geq e^{\lambda \epsilon} \mathbb{P}^{\nu, \pi} \left(C_{m,a}^\pi < \infty, \frac{1}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu) \geq \epsilon \right). \end{aligned}$$

By Proposition 7.6, for every $a \in \mathcal{A}$, $m \in \mathbb{N}^+$, and $\lambda \geq 0$,

$$\begin{aligned} \mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi < \infty\}} e^{-\frac{\lambda}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu)} \right) &\leq e^{\frac{(-\lambda)^2}{2m}}, \\ \mathbb{E}^{\nu, \pi} \left(\mathbb{I}_{\{C_{m,a}^\pi < \infty\}} e^{\frac{\lambda}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu)} \right) &\leq e^{\frac{\lambda^2}{2m}}. \end{aligned}$$

By rewriting the previous inequalities,

$$\begin{aligned}\mathbb{P}^{\nu,\pi}\left(C_{m,a}^\pi < \infty, \frac{1}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu) \leq -\epsilon\right) &\leq e^{\frac{\lambda^2}{2m} - \lambda\epsilon}, \\ \mathbb{P}^{\nu,\pi}\left(C_{m,a}^\pi < \infty, \frac{1}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu) \geq \epsilon\right) &\leq e^{\frac{\lambda^2}{2m} - \lambda\epsilon}.\end{aligned}$$

For every $\epsilon \geq 0$, let $\lambda = \epsilon m$, so that $\lambda \geq 0$. In that case,

$$\begin{aligned}\mathbb{P}^{\nu,\pi}\left(C_{m,a}^\pi < \infty, \frac{1}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu) \leq -\epsilon\right) &\leq e^{-\frac{m\epsilon^2}{2}}, \\ \mathbb{P}^{\nu,\pi}\left(C_{m,a}^\pi < \infty, \frac{1}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu) \geq \epsilon\right) &\leq e^{-\frac{m\epsilon^2}{2}}.\end{aligned}$$

□

Proposition 7.8. If ν is a 1-subgaussian stochastic bandit, then, for every $a \in \mathcal{A}$, $m \in \mathbb{N}^+$, and $\delta \in (0, 1]$,

$$\begin{aligned}\mathbb{P}^{\nu,\pi}\left(C_{m,a}^\pi < \infty, \frac{1}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu) \leq -\sqrt{\frac{2 \log(1/\delta)}{m}}\right) &\leq \delta, \\ \mathbb{P}^{\nu,\pi}\left(C_{m,a}^\pi < \infty, \frac{1}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu) \geq \sqrt{\frac{2 \log(1/\delta)}{m}}\right) &\leq \delta.\end{aligned}$$

Proof. Let $\delta \in (0, 1]$. If $\epsilon = \sqrt{2 \log(1/\delta)/m}$, then $\epsilon \geq 0$ and $\delta = e^{-\frac{m\epsilon^2}{2}}$, which implies the two inequalities. □

8 Upper confidence bounds

Consider a number of actions $n \in \mathbb{N}^+$, a set of actions $\mathcal{A} = \{1, \dots, n\}$, a stochastic bandit $\nu = (P_a \mid a \in \mathcal{A})$, a policy $\pi = (\pi_t \mid t \in \mathbb{N}^+)$, and a canonical triple $(\Omega, \mathcal{F}, \mathbb{P}^{\nu, \pi})$ for the stochastic bandit ν under the policy π .

Definition 8.1. The upper confidence bound $U_{t,a}^{\pi, \delta} : \Omega \rightarrow \mathbb{R}$ that policy π induces for action $a \in \mathcal{A}$ by time step $t \in \mathbb{N}^+$ with error $\delta \in (0, 1)$ is given by

$$U_{t,a}^{\pi, \delta}(\omega) = M_{t,a}^{\pi}(\omega) + \sqrt{\frac{2 \log(1/\delta)}{T_{t,a}^{\pi}(\omega)}}$$

whenever $T_{t,a}^{\pi}(\omega) > 0$. Intuitively, the role of $U_{t,a}^{\pi, \delta}$ is to overestimate μ_a^{ν} with high probability when δ is small.

Proposition 8.1. The upper confidence bound $U_{t,a}^{\pi, \delta} : \Omega \rightarrow \mathbb{R}$ that policy π induces for action $a \in \mathcal{A}$ by time step $t \in \mathbb{N}^+$ with error $\delta \in (0, 1)$ is given by

$$U_{t,a}^{\pi, \delta}(\omega) = \frac{1}{m} \sum_{k=1}^m X_{C_{k,a}^{\pi}}(\omega) + \sqrt{\frac{2 \log(1/\delta)}{m}}$$

whenever $T_{t,a}^{\pi}(\omega) = m$ for some $m \in \mathbb{N}^+$.

Proof. Let $\omega \in \Omega$, $a \in \mathcal{A}$, $t \in \mathbb{N}^+$, and $m \in \mathbb{N}^+$. If $T_{t,a}^{\pi}(\omega) = m$, then $C_{k,a}^{\pi}(\omega) \leq t$ for every $k \leq m$, so that

$$\sum_{k=1}^m X_{C_{k,a}^{\pi}}(\omega) = \sum_{k=1}^m X_{C_{k,a}^{\pi}}(\omega) \mathbb{I}_{\{C_{k,a}^{\pi} \leq t\}}(\omega) = \sum_{k=1}^m X_{C_{k,a}^{\pi}}(\omega) \sum_{t'=1}^t \mathbb{I}_{\{C_{k,a}^{\pi} = t'\}}(\omega) = \sum_{t'=1}^t X_{t'}(\omega) \sum_{k=1}^m \mathbb{I}_{\{C_{k,a}^{\pi} = t'\}}(\omega).$$

Note that $\{C_{k,a}^{\pi} = t'\} \cap \{C_{k',a}^{\pi} = t'\} = \emptyset$ if $k \neq k'$ and $t' \in \mathbb{N}^+$.

Let $t' \leq t$ and $A_{t'} = \pi_{t'}(X_0, \dots, X_{t'-1})$. Since $A_{t'}(\omega) = a$ if and only if $C_{k,a}^{\pi}(\omega) = t'$ for some $k \leq m$,

$$\sum_{k=1}^m X_{C_{k,a}^{\pi}}(\omega) = \sum_{t'=1}^t X_{t'}(\omega) \mathbb{I}_{\bigcup_{k=1}^m \{C_{k,a}^{\pi} = t'\}}(\omega) = \sum_{t'=1}^t X_{t'}(\omega) \mathbb{I}_{\{A_{t'} = a\}}(\omega).$$

Therefore, for every $\delta \in (0, 1)$,

$$U_{t,a}^{\pi, \delta}(\omega) = \frac{1}{T_{t,a}^{\pi}(\omega)} \sum_{k=1}^t X_k(\omega) \mathbb{I}_{\{A_k = a\}}(\omega) + \sqrt{\frac{2 \log(1/\delta)}{T_{t,a}^{\pi}(\omega)}} = \frac{1}{m} \sum_{k=1}^m X_{C_{k,a}^{\pi}}(\omega) + \sqrt{\frac{2 \log(1/\delta)}{m}}.$$

□

Definition 8.2. A policy π implements upper confidence bounds with error $\delta \in (0, 1)$ if, for every $t \in \mathbb{N}^+$,

$$\pi_t(X_0, \dots, X_{t-1}) = \begin{cases} t, & \text{if } t \leq n, \\ \arg \max_a U_{t-1,a}^{\pi, \delta}, & \text{if } t > n. \end{cases}$$

Note that $U_{t-1,a}^{\pi, \delta}$ is well-defined for every time step $t > n$ and action $a \in \mathcal{A}$.

Theorem 8.1. If ν is a 1-subgaussian stochastic bandit and the policy π implements upper confidence bounds with error $\delta = 1/t^2$ for some $t \in \mathbb{N}^+$, then

$$R_t^{\nu, \pi} \leq \left(3 \sum_{a=1}^n \Delta_a^{\nu} \right) + \sum_{a \mid \Delta_a^{\nu} > 0} \frac{16 \log(t)}{\Delta_a^{\nu}}.$$

Proof. If $t \leq n$, then $T_{t,a}^{\pi} \leq 1$ for every $a \in \mathcal{A}$, so that $R_t^{\nu, \pi} = \sum_a \Delta_a^{\nu} \mathbb{E}^{\nu, \pi}(T_{t,a}^{\pi}) \leq \sum_a \Delta_a^{\nu}$.

Let $t > n$ and consider an action $a \in \mathcal{A}$ such that $\Delta_a^{\nu} > 0$. For every $m \in \mathbb{N}^+$, since $T_{t,a}^{\pi} \leq t$,

$$\mathbb{E}^{\nu, \pi}(T_{t,a}^{\pi}) = \mathbb{E}^{\nu, \pi}(\mathbb{I}_{\{T_{t,a}^{\pi} > m\}} T_{t,a}^{\pi}) + \mathbb{E}^{\nu, \pi}(\mathbb{I}_{\{T_{t,a}^{\pi} \leq m\}} T_{t,a}^{\pi}) \leq t \mathbb{P}^{\nu, \pi}(T_{t,a}^{\pi} > m) + m.$$

Let $\delta = 1/t^2$ and $m = \lceil 8 \log(1/\delta)/(\Delta_a^\nu)^2 \rceil$, so that $m \in \mathbb{N}^+$. Furthermore, consider the event E given by

$$E = \left\{ \frac{1}{m} \sum_{k=1}^m X_{C_{k,a}^\pi} + \sqrt{\frac{2 \log(1/\delta)}{m}} < \mu_*^\nu \right\}.$$

Because the events E and E^c are disjoint,

$$\mathbb{P}^{\nu,\pi}(T_{t,a}^\pi > m) = \mathbb{P}^{\nu,\pi}(\{T_{t,a}^\pi > m\} \cap E) + \mathbb{P}^{\nu,\pi}(\{T_{t,a}^\pi > m\} \cap E^c).$$

We will consider the two terms on the right side of the equation above separately.

First, consider an action $a^* \in \mathcal{A}$ such that $\mu_{a^*}^\nu = \mu_*^\nu$, so that $a^* \neq a$. Furthermore, consider an $\omega \in E$ such that $T_{t,a}^\pi(\omega) > m$. In order to find a contradiction, suppose that $\mu_*^\nu < U_{t'-1,a^*}^{\pi,\delta}(\omega)$ for every $t' \in \mathbb{N}^+$ such that $n < t' \leq t$. Since $T_{t,a}^\pi(\omega) > m$, there is a $t' \in \mathbb{N}^+$ such that $C_{m+1,a}^\pi(\omega) = t'$ and $n < t' \leq t$. Therefore,

$$\pi_{t'}(X_0(\omega), \dots, X_{t'-1}(\omega)) = \arg \max_{a'} U_{t'-1,a'}^{\pi,\delta}(\omega) = a.$$

By Proposition 8.1, since $T_{t'-1,a}^\pi(\omega) = m$ and $\omega \in E$,

$$U_{t'-1,a}^{\pi,\delta}(\omega) = \frac{1}{m} \sum_{k=1}^m X_{C_{k,a}^\pi}(\omega) + \sqrt{\frac{2 \log(1/\delta)}{m}} < \mu_*^\nu < U_{t'-1,a^*}^{\pi,\delta}(\omega),$$

which is a contradiction because $U_{t'-1,a}^{\pi,\delta}(\omega) = \sup_{a'} U_{t'-1,a'}^{\pi,\delta}(\omega)$.

Therefore, if $\omega \in E$ and $T_{t,a}^\pi(\omega) > m$, then $\mu_*^\nu \geq U_{t'-1,a^*}^{\pi,\delta}(\omega)$ for some $t' \in \mathbb{N}^+$ such that $n < t' \leq t$. Consequently, there is an $m' \in \mathbb{N}^+$ such that $m' \leq t$ and $T_{t,a^*}^\pi(\omega) \geq m'$ and

$$\mu_*^\nu \geq \frac{1}{m'} \sum_{k=1}^{m'} X_{C_{k,a^*}^\pi}(\omega) + \sqrt{\frac{2 \log(1/\delta)}{m'}}.$$

From the previous statement,

$$\mathbb{P}^{\nu,\pi}(\{T_{t,a}^\pi > m\} \cap E) \leq \mathbb{P}^{\nu,\pi} \left(\bigcup_{m' \leq t} \left\{ T_{t,a^*}^\pi \geq m', \mu_*^\nu \geq \frac{1}{m'} \sum_{k=1}^{m'} X_{C_{k,a^*}^\pi} + \sqrt{\frac{2 \log(1/\delta)}{m'}} \right\} \right).$$

By the union bound, the fact that $T_{t,a^*}^\pi(\omega) \geq m'$ implies $C_{m',a^*}^\pi(\omega) < \infty$, and Proposition 7.8,

$$\mathbb{P}^{\nu,\pi}(\{T_{t,a}^\pi > m\} \cap E) \leq \sum_{m' \leq t} \mathbb{P}^{\nu,\pi} \left(C_{m',a^*}^\pi < \infty, \mu_*^\nu \geq \frac{1}{m'} \sum_{k=1}^{m'} X_{C_{k,a^*}^\pi} + \sqrt{\frac{2 \log(1/\delta)}{m'}} \right) \leq t\delta.$$

Second, consider an $\omega \in E^c$ such that $T_{t,a}^\pi(\omega) > m$. Since $C_{m,a}^\pi(\omega) < \infty$,

$$\mathbb{P}^{\nu,\pi}(\{T_{t,a}^\pi > m\} \cap E^c) \leq \mathbb{P}^{\nu,\pi}(\{C_{m,a}^\pi < \infty\} \cap E^c) = \mathbb{P}^{\nu,\pi} \left(C_{m,a}^\pi < \infty, \frac{1}{m} \sum_{k=1}^m X_{C_{k,a}^\pi} + \sqrt{\frac{2 \log(1/\delta)}{m}} \geq \mu_*^\nu \right).$$

By subtracting $\mu_a^\nu + \sqrt{2 \log(1/\delta)/m}$ from both sides of an inequality above and the definition of Δ_a^ν ,

$$\mathbb{P}^{\nu,\pi}(\{T_{t,a}^\pi > m\} \cap E^c) \leq \mathbb{P}^{\nu,\pi} \left(C_{m,a}^\pi < \infty, \frac{1}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu) \geq \Delta_a^\nu - \sqrt{\frac{2 \log(1/\delta)}{m}} \right).$$

Since $m \geq 8 \log(1/\delta)/(\Delta_a^\nu)^2$, note that $\sqrt{2 \log(1/\delta)/m} \leq \Delta_a^\nu/2 = \Delta_a^\nu - \Delta_a^\nu/2$ and

$$\Delta_a^\nu - \sqrt{\frac{2 \log(1/\delta)}{m}} \geq \frac{\Delta_a^\nu}{2}.$$

Therefore, by the previous inequality and Proposition 7.7,

$$\mathbb{P}^{\nu, \pi} (\{T_{t,a}^\pi > m\} \cap E^c) \leq \mathbb{P}^{\nu, \pi} \left(C_{m,a}^\pi < \infty, \frac{1}{m} \sum_{k=1}^m (X_{C_{k,a}^\pi} - \mu_a^\nu) \geq \frac{\Delta_a^\nu}{2} \right) \leq e^{-\frac{m(\Delta_a^\nu)^2}{8}}.$$

By returning to a previous equation,

$$\mathbb{P}^{\nu, \pi} (T_{t,a}^\pi > m) = \mathbb{P}^{\nu, \pi} (\{T_{t,a}^\pi > m\} \cap E) + \mathbb{P}^{\nu, \pi} (\{T_{t,a}^\pi > m\} \cap E^c) \leq t\delta + e^{-\frac{m(\Delta_a^\nu)^2}{8}}.$$

By returning to a previous inequality, since $\delta = 1/t^2$,

$$\mathbb{E}^{\nu, \pi} (T_{t,a}^\pi) \leq t\mathbb{P}^{\nu, \pi} (T_{t,a}^\pi > m) + m \leq te^{-\frac{m(\Delta_a^\nu)^2}{8}} + m + 1.$$

Since $m \geq 8 \log(1/\delta)/(\Delta_a^\nu)^2$ implies $-m(\Delta_a^\nu)^2/8 \leq \log \delta$,

$$\mathbb{E}^{\nu, \pi} (T_{t,a}^\pi) \leq t\delta + m + 1 = \frac{1}{t} + m + 1 \leq 2 + m \leq 3 + \frac{8 \log(1/\delta)}{(\Delta_a^\nu)^2} = 3 + \frac{16 \log(t)}{(\Delta_a^\nu)^2}.$$

For every $t > n$, since $\mathbb{E}^{\nu, \pi} (T_{t,a}^\pi) \leq 3 + 16 \log(t)/(\Delta_a^\nu)^2$ for every $a \in \mathcal{A}$ such that $\Delta_a^\nu > 0$,

$$R_t^{\nu, \pi} = \sum_{a|\Delta_a^\nu > 0} \Delta_a^\nu \mathbb{E}^{\nu, \pi} (T_{t,a}^\pi) \leq \sum_{a|\Delta_a^\nu > 0} \Delta_a^\nu \left(3 + \frac{16 \log(t)}{(\Delta_a^\nu)^2} \right) = \left(3 \sum_{a=1}^n \Delta_a^\nu \right) + \sum_{a|\Delta_a^\nu > 0} \frac{16 \log(t)}{\Delta_a^\nu}.$$

□

Theorem 8.2. If ν is a 1-subgaussian stochastic bandit and the policy π implements upper confidence bounds with error $\delta = 1/t^2$ for some $t \in \mathbb{N}^+$, then

$$R_t^{\nu, \pi} \leq 8\sqrt{tn \log(t)} + 3 \sum_{a=1}^n \Delta_a^\nu.$$

Proof. If $t \leq n$, then $T_{t,a}^\pi \leq 1$ for every $a \in \mathcal{A}$, so that $R_t^{\nu, \pi} = \sum_a \Delta_a^\nu \mathbb{E}^{\nu, \pi} (T_{t,a}^\pi) \leq \sum_a \Delta_a^\nu$.

Let $t > n$. For every $\Delta > 0$, since $\sum_a \mathbb{E}^{\nu, \pi} (T_{t,a}^\pi) = t$,

$$R_t^{\nu, \pi} = \left(\sum_{a|\Delta_a^\nu < \Delta} \Delta_a^\nu \mathbb{E}^{\nu, \pi} (T_{t,a}^\pi) \right) + \left(\sum_{a|\Delta_a^\nu \geq \Delta} \Delta_a^\nu \mathbb{E}^{\nu, \pi} (T_{t,a}^\pi) \right) \leq t\Delta + \sum_{a|\Delta_a^\nu \geq \Delta} \Delta_a^\nu \mathbb{E}^{\nu, \pi} (T_{t,a}^\pi).$$

From the proof of Theorem 8.1, recall that $\mathbb{E}^{\nu, \pi} (T_{t,a}^\pi) \leq 3 + 16 \log(t)/(\Delta_a^\nu)^2$ if $\Delta_a^\nu > 0$. Therefore,

$$R_t^{\nu, \pi} \leq t\Delta + \sum_{a|\Delta_a^\nu \geq \Delta} \Delta_a^\nu \left(3 + \frac{16 \log(t)}{(\Delta_a^\nu)^2} \right) \leq t\Delta + \left(\sum_{a|\Delta_a^\nu \geq \Delta} \frac{16 \log(t)}{\Delta_a^\nu} \right) + 3 \sum_{a=1}^n \Delta_a^\nu.$$

Let $\Delta = \sqrt{16n \log(t)}/t$, so that $\Delta > 0$. Since $\Delta_a^\nu \geq \Delta$ implies $16 \log(t)/\Delta_a^\nu \leq 16 \log(t)/\Delta$,


$$R_t^{\nu, \pi} \leq t\Delta + \frac{16n \log(t)}{\Delta} + 3 \sum_{a=1}^n \Delta_a^\nu = \sqrt{t} \sqrt{16n \log(t)} + \sqrt{t} \sqrt{16n \log(t)} + 3 \sum_{a=1}^n \Delta_a^\nu = 8\sqrt{tn \log(t)} + 3 \sum_{a=1}^n \Delta_a^\nu.$$

□

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