Convex functions & comparison to the best convex vector

↳ efficient forecaster (but worse bound...)

$\mathcal{X} = \{ (p_1 \dots p_N) : \sum_j p_j = 1, \ \forall k \ p_k \geq 0 \}$ is the simplex of convex weight vectors.

Setting (reminder): At each round $t = 1, 2, \dots T$:

1. The Statistician and the opponent pick simultaneously $p_t \in \mathcal{X}$ and a convex loss function $\ell_t : \mathcal{X} \to [m, M]$
2. ℓ_t and p_t are revealed

↳ Regret: $R_T = \sum_{t=1}^{T} \ell_t(p_t) - \inf_{p \in \mathcal{X}} \sum_{t=1}^{T} \ell_t(p)$ to be controlled in a uniform way

Fact: Convex functions are subdifferentiable on the interior of their domain of definition:

Let $f : \mathcal{D} \to \mathbb{R}$ be convex, where $\mathcal{D} \subseteq \mathbb{R}^N$ is convex:

$$\forall x \in \mathring{\mathcal{D}}, \quad \exists \partial f_x \in \mathbb{R}^N \ \Big| \ \forall y \in \mathcal{D}, \quad f(x) - f(y) \leq \partial f_x \cdot (x - y)$$

$\partial f(x) = \{$ the set of all possible such $\partial f_x \}$ is called the subgradient of f at x

If f is differentiable at x, then $\partial f(x) = \{ \nabla f(x) \}$.

Ex: $f(x) = |x|$, $\partial f(x) = \begin{cases} \{-1\} & \text{if } x < 0 \\ \{1\} & \text{if } x > 0 \\ [-1, 1] & \text{if } x = 0 \end{cases}$

Application: If $p_t \in \mathring{\mathcal{X}}$ (ie, $p_{jt} > 0 \ \forall j$) then $\exists \, \partial \ell_t(p_t) \in \mathbb{R}^N \ \Big|$

$$\forall p \in \mathcal{X}, \quad \ell_t(p_t) - \ell_t(p) \leq \partial \ell_t(p_t) \cdot (p_t - p)$$

Example: Meta-statistical framework: $\ell_t(p) = \left(\sum_j p_j f_{jt} - y_t \right)^2$

ℓ_t is differentiable, $\nabla \ell_t(p) = \left(2 \left(\sum_j p_j f_{jt} - y_t \right) f_{jt} \right)_j$

↳ Gradients in $[-G, G]^N$ with $G = 2B^2$ if $f_{jt}, y_t \in [0, B]$

Strategy: Exponentiated Gradients (EG) with learning rate $\eta > 0$

$p_1 = (1/N, \dots 1/N)$ and

$$p_{jt} = \exp\Big(-\eta \sum_{s=1}^{t-1} (\partial \ell_s(p_s))_j\Big) \Big/ \sum_{k=1}^{N} \exp\Big(-\eta \sum_{s=1}^{t-1} (\partial \ell_s(p_s))_k\Big)$$

→ strategy easy to implement as soon as subgradients can be easily computed.

Theorem: Assume that the ℓ_t are picked such that

$$\forall t, \forall j, \forall p \in \mathring{\mathcal{X}}, \qquad (\partial \ell_t(p))_j \in [-G, G]$$

Then the regret of EG tuned with $\eta > 0$ is controled as

$$R_T = \sum_{t=1}^{T} \ell_t(p_t) - \inf_{p \in \mathcal{X}} \sum_{t=1}^{T} \ell_t(p) \leqslant \frac{\ln N}{\eta} + \eta \frac{G^2}{2} T$$

In particular, the choice $\eta = \frac{1}{G}\sqrt{\frac{2 \ln N}{T}}$ leads to

$$R_T \leqslant G\sqrt{2T \ln N}$$

Proof: Fix a p. Since by construction (cf. exponential weights), $p_t \in \mathring{\mathcal{X}}$ we have

$$\ell_t(p_t) - \ell_t(p) \leqslant \partial \ell_t(p_t) \cdot (p_t - p)$$

Thus

$$R_T \leqslant \sup_{p \in \mathcal{X}} \sum_{t=1}^{T} \partial \ell_t(p_t) \cdot (p_t - p)$$

$$= \sup_{p \in \mathcal{X}} \sum_{t=1}^{T} \sum_{j=1}^{N} p_{jt} \tilde{\ell}_{jt} - \sum_{t=1}^{T} \sum_{j=1}^{N} p_j \tilde{\ell}_{jt}$$

where we denoted by $\tilde{\ell}_{jt} = (\partial \ell_t(p_t))_j$ the components of the subgradients: we interpret them as pseudo-losses

By linearity in p of the last upper bound,

$$R_T \leqslant \sup_{p \in \mathcal{X}} \sum_{t=1}^{T} \sum_{j=1}^{N} p_{jt} \tilde{\ell}_{jt} - \sum_{t=1}^{T} \sum_{j} p_j \tilde{\ell}_{jt} = \sum_{t,j} p_{jt} \tilde{\ell}_{jt} - \min_k \sum_{t=1}^{T} \tilde{\ell}_{kt}$$

↳ We have performed a reduction to the linear case with vectors of losses $(\tilde{\ell}_{1t} \ldots \tilde{\ell}_{Nt})$ where $\tilde{\ell}_{jt} \in [-G, G]$

hence the stated bound.

Application: Oracle inequalities → From individual sequences to stochastic sequences

Question: Let $(Y_1 \dots Y_T)$ be a sequence of iid random variables taking values in an arbitrary set $\mathcal{Y}$; and $Q : \mathcal{X} \times \mathcal{Y} \to \mathbb{R}$ be a bounded loss function, convex in its first argument, with bounded subgradients:

$$G = \sup_{y \in \mathcal{Y}} \sup_{p \in \mathring{\mathcal{X}}} \| \partial Q(p, y) \|_\infty < +\infty$$

Aim: Construct $\hat{\theta}_T = \hat{\theta}_T(Y_1 \dots Y_T)$ such that

$$\mathbb{E}\left[Q(\hat{\theta}_T, Y) \right] \leq \inf_{\theta \in \mathcal{X}} \mathbb{E}\left[Q(\theta, Y) \right] + \varepsilon_T$$

where Y is independent of the Y_t with the same distribution and $\varepsilon_T \searrow 0$.

(The expectation $\mathbb{E}$ is w.r.t. $Y_1 \dots Y_T$ and Y.)

Typical machine learning method: Empirical risk minimization, possibly in a regularized way:

$$\hat{\theta}_T \in \underset{\theta \in \mathcal{X}}{\operatorname{argmin}} \left\{ \frac{1}{T} \sum_{t=1}^{T} Q(\theta, Y_t) + \lambda \operatorname{reg}(\theta) \right\}$$

with $\operatorname{reg}(\theta) = \|\theta\|_2$ or $\|\theta\|_1$ or ...

and λ to be tuned (called the regularization factor)

Our method: (as in our proof of Sion's lemma)

1) Pretend data is sequential, while of course it is batch

$$\tilde{\theta}_1 = (1/N, \dots 1/N) \quad \text{and by induction, with } \eta = \frac{1}{G}\sqrt{\frac{2 \ln N}{T}} :$$

$$\tilde{\theta}_{j,t} = \exp\left(-\eta \sum_{s=1}^{t-1} \left(\partial Q(\tilde{\theta}_s, Y_s)\right)_j\right) \Big/ \sum_{k=1}^{N} \exp\left(-\eta \sum_{s=1}^{t-1} \left(\partial Q(\tilde{\theta}_s, Y_s)\right)_k\right)$$

2) Consider an average: $\hat{\theta}_T = \frac{1}{T} \sum_{t=1}^{T} \tilde{\theta}_t$

(note: we do not use y_T!)

Guarantee: $\varepsilon_T = G\sqrt{\frac{2\ln N}{T}}$

Proof: By the theorem on EG (exponentiated gradient) and given our choice of η:

$$\sum_{t=1}^{T} Q(\tilde{\theta}_t, y_t) - \inf_{\theta \in \mathcal{X}} \sum_{t=1}^{T} Q(\theta, y_t) \leqslant G\sqrt{2T\ln N}$$

Thus: $\forall \theta \in \mathcal{X}$, $\quad \frac{1}{T}\sum_{t=1}^{T} Q(\tilde{\theta}_t, y_t) \leqslant \frac{1}{T}\sum_{t=1}^{T} Q(\theta, y_t) + \varepsilon_T$

with $\varepsilon_T = G\sqrt{\frac{2\ln N}{T}}$

Now, since $y_1, \dots, y_T$ and y are iid:

$$\mathbb{E}\left[\frac{1}{T}\sum_{t=1}^{T} Q(\theta, y_t)\right] = \mathbb{E}\left[Q(\theta, y)\right]$$

We conclude the proof by showing that $\mathbb{E}\left[\frac{1}{T}\sum_{t=1}^{T} Q(\tilde{\theta}_t, y_t)\right] \geqslant \mathbb{E}\left[Q(\hat{\theta}_T, y)\right]$

Indeed: $\mathbb{E}\left[\frac{1}{T}\sum_{t=1}^{T} Q(\tilde{\theta}_t, y_t)\right] = \mathbb{E}\left[\underbrace{\frac{1}{T}\sum_{t=1}^{T} Q(\tilde{\theta}_t, y)}_{\geqslant Q\left(\frac{1}{T}\sum_t \tilde{\theta}_t,\, y\right)}\right]$

$\tilde{\theta}_t$ only depends on $y_1, \dots, y_{t-1}$ and $(y_1, \dots, y_{t-1}, y_t)$ and $(y_1, \dots, y_{t-1}, y)$ have the same distribution

by convexity and because the second argument is now the same for everyone!

We discard all measurability issues by rewriting $\mathbb{E}\left[\inf_{\theta} \sum_t Q(\theta, y_t)\right]$ but by considering each θ separately

Extension: Oracle inequality for stationary data.

A stationary sequence $(y_1, y_2, \dots)$ is by definition a sequence of random variables such that

$\forall k \geqslant 1, \quad \forall t \geqslant 1, \quad (y_1, \dots, y_k)$ and $(y_{t+1}, \dots, y_{t+k})$ have the same distribution.

* **Proof of performance?** ($\longrightarrow$ explains where the construction comes from!)

What does EG guarantee?

$$\forall \theta \in \mathcal{X}, \qquad \frac{1}{T}\sum_{t=1}^{T} Q\big(\psi_t^{EG}(y_1, \dots y_{t-1}),\ y_t\big)$$

$$\leqslant \frac{1}{T}\sum_{t=1}^{T} Q(\theta, y_t) + \varepsilon_T$$

still $G\sqrt{(2\ln N)/T}$

We take expectations in both sides to conclude:

- Stationarity implies in particular that all the y_t have the same distribution (but they are NOT independent in general); hence

$$\mathbb{E}\Big[\frac{1}{T}\sum_{t=1}^{T} Q(\theta, y_t)\Big] = \mathbb{E}\big[Q(\theta, y_{T+1})\big]$$

- it also implies that $\big(\psi_t^{EG}(y_1, \dots y_{t-1}),\ y_t\big)$ and $\big(\psi_t^{EG}(y_{T+2-t}, \dots y_T),\ y_{T+1}\big) = \big(\tilde{\theta}_t, y_{T+1}\big)$ have the same distribution, so that

$$\mathbb{E}\Big[\frac{1}{T}\sum_{t=1}^{T} Q\big(\psi_t^{EG}(y_1, \dots y_{t-1}),\ y_t\big)\Big]$$

$$= \mathbb{E}\Big[\frac{1}{T}\sum_{t=1}^{T} Q(\tilde{\theta}_t, y_{T+1})\Big] \underset{\substack{\text{convexity} \\ \text{of } \theta \mapsto Q(\theta, y_{T+1})}}{\geqslant} \mathbb{E}\big[Q(\hat{\theta}_T, y_{T+1})\big]$$

- thus we proved, for our choice of $\hat{\theta}_T$:

$$\mathbb{E}\big[Q(\hat{\theta}_T, y_{T+1})\big] \leqslant \inf_{\theta \in \mathcal{X}} \mathbb{E}\big[Q(\theta, y_{T+1})\big] + \varepsilon_T$$

same ε_T as for the iid case.

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For a sequence of observations $z_1, \ldots z_t \in \mathcal{Y}$, EG outputs the following weights, which we re-define as functions of the information available:

$$\psi_1^{EG} = (1/N, \ldots 1/N)$$

and for $t \geq 2$:

$$\psi_{jt}^{EG}(z_1, \ldots z_{t-1}) = \frac{\exp\left(-\eta \sum_{s=1}^{t-1} \left(\partial Q(\psi_s^{EG}(z_1 \ldots z_{s-1}), z_s)\right)_j\right)}{\sum_{k=1}^{N} \exp\left(-\eta \sum_{s=1}^{t-1} \left(\partial Q(\psi_s^{EG}(z_1 \ldots z_{s-1}), z_s)\right)_k\right)}$$

j-th component of $\psi_t^{EG}(z_1 \ldots z_{t-1}) \in \mathbb{R}^N$

ψ_t^{EG} is an extremely complicated function of its arguments $z_1 \ldots z_{t-1}$ (cf. the various calls to ψ_s^{EG}, with $s \leq t-1$, in its definition).

We define $\tilde{\theta}_t = \psi_t^{EG}(y_{T+2-t}, \ldots y_T)$ for $t \geq 2$

and $\tilde{\theta}_1 = (1/N, \ldots 1/N)$

We recommend: $\hat{\theta}_T = \frac{1}{T} \sum_{t=1}^{T} \tilde{\theta}_t$

Computing $\hat{\theta}_T$ is costly: the computation of each $\tilde{\theta}_t$ requires $t-1$ steps, namely the computation of the

$\psi_s^{EG}(y_{T+2-t}, \ldots y_{T-t+s})$ for $2 \leq s \leq t$

no such intermediate quantity appears twice

$\Rightarrow$ about $\sum_{t=1}^{T} (t-1) = O(T^2/2)$ computation steps required.

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Optimality of the $\sqrt{\frac{T}{2}\ln N}$ bound: asymptotic lower bound.

In the case of linear losses

By homogeneity we may assume that $\ell_{jt} \in [0,1]$ (ie, $m=0$ and $M=1$) for all t and j.

Theorem: All forecasting strategies of the Statistician are such that

$$1 \leqslant \liminf_{N\to+\infty} \; \liminf_{T\to+\infty} \; \sup_{\ell_{jt}\in[0,1]} \frac{\displaystyle\sum_{t,j} p_{jt}\,\ell_{jt} - \min_k \sum_{t=1}^{T} \ell_{kt}}{\sqrt{\frac{T}{2}\ln N}}$$

the opponent does not need to react, it suffices to consider fixed-in-advance sequences (individual sequences)

Proof: We lower bound the $\sup_{\ell_{jt}}$ by an expectation $\mathbb{E}$, assuming that the losses are given by random variables L_{jt} iid $\sim$ Ber(1/2)

$\mathcal{F}_{t-1} = \sigma\big(L_{js},\ s\leq t-1 \text{ and } j\in\{1,\dots,N\}\big)$ is the information available at the beginning of round t: thus, p_t is $\mathcal{F}_{t-1}$-measurable and by the tower rule,

$$\mathbb{E}\Big[\sum_j p_{jt}L_{jt}\Big] = \mathbb{E}\Big[\sum_j p_{jt}\,\underbrace{\mathbb{E}\big[L_{jt}\mid\mathcal{F}_{t-1}\big]}_{=\mathbb{E}[L_{jt}]=1/2}\Big] = 1/2$$

and by independence: $p_{jt} \perp\!\!\!\perp L_{jt}$

$[p_{jt}L_{jt}] = \mathbb{E}[p_{jt}]\,\mathbb{E}[L_{jt}] = \mathbb{E}[p_{jt}]\,1/2$

$\sum_j \mathbb{E}[p_{jt}L_{jt}] = 1/2$

not so surprising: you cannot predict iid random variables!

* But *

we will show that

$\mathbb{E}\Big[\min_k \sum_{t=1}^{T} L_{kt}\Big]$ is smaller than $T/2$, even if "individually", we have $\forall k$, $\mathbb{E}\Big[\sum_{t=1}^{T} L_{kt}\Big] = T/2$

"crowd" effect (due to the central limit theorem)

Let us summarize what we have so far:

worst-case regret $= \sup_{\ell_{jt} \in [0,1]} \left\{ \sum_{j,t} p_{jt} \ell_{jt} - \min_k \sum_{t=1}^{T} \ell_{kt} \right\} \geq \mathbb{E}\left[\sum_{j,t} p_{jt} L_{jt} - \min_k \sum_{t=1}^{T} L_{kt} \right]$

$$= \frac{T}{2} - \mathbb{E}\left[\min_k \sum_{t=1}^{T} L_{kt} \right]$$

$$= \frac{\sqrt{T}}{2} \, \mathbb{E}\left[\max_{k=1..N} \frac{\sum_{t=1}^{T} \left(\frac{1}{2} - L_{kt} \right)}{\frac{1}{2}\sqrt{T}} \right]$$

note that $\mathbb{E}[Z_{kT}] = 0$ and $\mathrm{Var}(Z_{kT}) = 1$ by independence

we denote $Z_{kT} = \dfrac{\sum_{t=1}^{T} \left(\frac{1}{2} - L_{kt} \right)}{\frac{1}{2}\sqrt{T}}$

By the central limit theorem, $Z_{kT} \xrightarrow[T \to +\infty]{\mathcal{L}} \mathcal{N}(0,1)$

We will show successively that

it would be sufficient to prove $\liminf_{T\to+\infty} \mathbb{E}[\max_k Z_{kT}] \geq \mathbb{E}[\max G_k]$ $\longrightarrow$ (1) $\mathbb{E}\left[\max_{k=1..N} Z_{kT} \right] \xrightarrow[T \to +\infty]{} \mathbb{E}\left[\max_{k \leq N} G_k \right]$

where $G_1 \ldots G_k$ iid $\sim \mathcal{N}(0,1)$

it would be sufficient to prove $\liminf_{N\to+\infty} \dfrac{\mathbb{E}[\max_{k\leq N} G_k]}{\sqrt{2\ln N}} \geq 1$ $\longrightarrow$ (2) $\mathbb{E}\left[\max_{k \leq N} G_k \right] \underset{N \to +\infty}{\sim} \sqrt{2 \ln N}$

Which will conclude the proof of the theorem.

Point (1) relies on asymptotic uniform integrability.

Note: in general, $Y_T \xrightarrow{\mathcal{L}} Y$ does NOT imply $\mathbb{E}f(Y_T) \to \mathbb{E}f(Y)$ if f is just assumed continuous.
Ex: $Y_T = T^2 \mathbb{1}_{\{U_T \in [0, 1/T]\}}$ where U_t iid $\sim \mathcal{U}_{[0,1]}$
We have $Y_T \to 0$ in probability but $\mathbb{E} Y_T = T \to +\infty$

Reminder: If $(Y_T)_{T \geq 1}$ is a sequence of $\mathbb{R}^N$-valued random variables with $Y_T \xrightarrow[T \to +\infty]{\mathcal{L}} Y$, then for all continuous and bounded functions $f : \mathbb{R}^N \to \mathbb{R}$,

$$\mathbb{E}[f(Y_T)] \longrightarrow \mathbb{E}[f(Y)]$$

Here: $Y_T = (Z_{kT})_{k \in \{1, \ldots, N\}} \in \mathbb{R}^N$

and $Y_T \xrightarrow{\mathcal{L}} \begin{bmatrix} G_1 \\ \vdots \\ G_N \end{bmatrix} \sim \mathcal{N}(0, I_N)$ by independence of the components

* but * $f(z_1 \dots z_N) = \max_{k \leq N} z_k$ is not bounded (though being continuous).

Definition: $(f(Y_T))_{T \geq 1}$ is a.u.i. (asymptotically uniformly integrable)

if $\lim_{L \to +\infty} \limsup_{T \to +\infty} \mathbb{E}\Big[|f(Y_T)| \, \mathbb{1}_{\{|f(Y_T)| > L\}} \Big] = 0$

Lemma: If $\left\{ \begin{array}{l} Y_T \xrightarrow{\mathcal{L}} Y \\ (f(Y_T)) \text{ is u.a.i} \\ f \text{ continuous} \end{array} \right\}$ then (a) $f(Y) \in \mathbb{L}^1$ and $f(Y_T) \in \mathbb{L}^1$ $\forall T$ suff. large

and (b) $\mathbb{E}[f(Y_T)] \xrightarrow[T \to +\infty]{} \mathbb{E}[f(Y)]$

(a): see an added page later in this document

Proof: $\hookrightarrow$ (b) We may assume with no loss of generality that $f \geq 0$

(otherwise, we consider $f^+ = \max\{f, 0\}$ and $f^- = \max\{-f, 0\}$ the positive and negative parts of f; and use $f = f^+ - f^-$ and the fact that $f(Y) \in \mathbb{L}^1$)

$-$: $\big| \mathbb{E}[f(Y)] - \mathbb{E}[f(Y_T)] \big|$

$\leq \big| \mathbb{E}[f(Y)] - \mathbb{E}[\min\{f(Y), L\}] \big|$

$+ \big| \mathbb{E}[\min\{f(Y), L\}] - \mathbb{E}[\min\{f(Y_T), L\}] \big|$ $\rightsquigarrow$ tends to 0 as $T \to +\infty$, since $\min\{f(\cdot), L\}$ is continuous, bounded in $[0, L]$; and $Y_T \xrightarrow{\mathcal{L}} Y$

$+ \big| \mathbb{E}[\min\{f(Y_T), L\}] - \mathbb{E}[f(Y_T)] \big|$

Thus, $\forall L$: $\limsup_{T \to +\infty} \big| \mathbb{E}[f(Y)] - \mathbb{E}[f(Y_T)] \big|$

$\leq \big| \mathbb{E}[f(Y)] - \mathbb{E}[\min\{f(Y), L\}] \big|$

$+ \limsup_{T \to +\infty} \big| \mathbb{E}[\min\{f(Y_T), L\}] - \mathbb{E}[f(Y_T)] \big|$

Taking $\limsup_{L \to +\infty}$ in both sides (the left-hand side is independent of L)

and using that $\limsup_{T \to +\infty} (a_T + b_T) \leq \limsup_{T \to +\infty} a_T + \limsup_{T \to +\infty} b_T$

[think in terms of largest adherence values]

we get

$$\limsup_{T \to +\infty} \big| \mathbb{E}[f(Y)] - \mathbb{E}[f(Y_T)] \big| \leq \limsup_{L \to +\infty} \big| \mathbb{E}[f(Y)] - \mathbb{E}[\min\{f(Y), L\}] \big| + \limsup_{L} \limsup_{T} \big| \mathbb{E}[\min\{f(Y_T), L\}] - \mathbb{E}[f(Y_T)] \big|$$

By monotone convergence, (or dominated)
$$\mathbb{E}\big[\min\{f(Y),L\}\big] \xrightarrow[L\to+\infty]{} \mathbb{E}\big[f(Y)\big]$$

And by the u.a.i property,
$$\limsup_{L\to+\infty}\ \limsup_{T\to+\infty}\ \Big|\underbrace{\mathbb{E}\big[\min\{f(Y_T),L\}\big]-\mathbb{E}\big[f(Y_T)\big]}\Big| = 0$$
$$= \Big|\mathbb{E}\big[(f(Y_T)-L)\,\mathbb{1}_{\{f(Y_T)>L\}}\big]\Big|$$
because f assumed ≥ 0
$$\leq \mathbb{E}\big[f(Y_T)\,\mathbb{1}_{\{f(Y_T)>L\}}\big]$$

Application: Need only to check that $\max_{k\leq N} Z_{kT}$ is u.a.i to get (1) from the lemma.

Indeed, given $L>0$,
$$\mathbb{E}\Big[\big|\max_{k\leq N} Z_{kT}\big|\,\mathbb{1}_{\{|\max_{k\leq N} Z_{kT}|>L\}}\Big]$$
$$= \int_0^{+\infty} \mathbb{P}\Big(\underbrace{\big|\max_{k\leq N} Z_{kT}\big|\,\mathbb{1}_{\{|\max_{k\leq N} Z_{kT}|>L\}} \geq u}\Big)\,du$$

a well-known fact: if $X\geq 0$, $\mathbb{E}[X]=\int_0^{+\infty}\mathbb{P}(X\geq u)\,du$

Indeed, by Fubini-Tonelli:
$$\mathbb{E}[X] = \int_{[0,+\infty)} x\,d\mathbb{P}^X(x) = \int_{[0,+\infty)^2} \mathbb{1}_{\{0\leq u\leq x\}}\,d\mathbb{P}^X(x)\,du$$
$$= \int_{[0,+\infty)} \mathbb{P}(X\geq u)\,du$$

equals
$$\begin{cases} \mathbb{P}\big(\big|\max_{k\leq N} Z_{kT}\big|>L\big) & \text{if } u\leq L \\ \mathbb{P}\big(\big|\max_{k\leq N} Z_{kT}\big|\geq u\big) & \text{if } u>L \end{cases}$$

But, for all $u>0$:
$$\mathbb{P}\big(\big|\max_{k\leq N} Z_{kT}\big|\geq u\big) \leq \mathbb{P}\big(\exists j\leq N \mid |Z_{jT}|\geq u\big)$$
$$\leq N \times \mathbb{P}\big(|Z_{1T}|\geq u\big)$$
$$\leq N \times \frac{\operatorname{Var} Z_{1T}}{u^2} = N/u^2$$
union bound + same distribution

$\mathbb{E}Z_{1T}=0$ and Tchebychev

cf. $\operatorname{Var} Z_{1T}=1$

Substituting above, the conclusion is obtained:
$$\mathbb{E}\Big[\big|\max_{k\leq N} Z_{kT}\big|\,\mathbb{1}_{\{|\max_{k\leq N} Z_{kT}|>L\}}\Big] \leq \int_0^L \frac{N}{L^2}\,du + \int_L^{+\infty}\frac{N}{u^2}\,du = \frac{2N}{L}$$
bound independent of T and such that $\to 0$ as $L\to+\infty$

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Alternative way:

$$\mathbb{E}\Big[\big|\max_{k \le N} Z_{kt}\big| \, \mathbb{1}_{\{|\max_{k\le N} Z_{kt}| > L\}} \Big]$$

$$\underset{\text{Cauchy-Schwarz}}{\le} \underbrace{\Big(\mathbb{E}\Big[\max_{k\le N} Z_{kt}^2\Big]\Big)^{1/2}}_{\le \left(\sum_{k \le N} \mathbb{E} Z_{kt}^2\right)^{1/2} = \left(N \, \mathrm{Var}(Z_{1t})\right)^{1/2} = N^{1/2}} \underbrace{\Big(\mathbb{P}\Big\{ \big|\max_{k\le N} Z_{kt}\big| > L \Big\}\Big)^{1/2}}_{\le \sqrt{N}/L \text{ as proved above}} \le N/L \longrightarrow 0$$

Note (credits: Clement Berenfeld + Chenlin Gu.)

follows from $Y_T \to Y$ & f continuous

Proof of property (a): $(f(Y_T))$ u.a.i and $f(Y_T) \to f(Y)$

implies $f(Y) \in \mathbb{L}^1$ (and $f(Y_T) \in \mathbb{L}^1$ $\forall T$ sufficiently large)

Indeed: By uai, $\exists L_0 \mid \limsup_{T \to +\infty} \mathbb{E}\big[|f(Y_T)| \, \mathbb{1}_{\{|f(Y_T)| > L_0\}} \big] < +\infty$

in particular, $\limsup_{T \to +\infty} \mathbb{E}\big[|f(Y_T)| \big] < +\infty$

Thus, $\big(\mathbb{E}[|f(Y_T)|] \big)_{T \geqslant 1}$ is bounded

By Skorokhod, we can assume with no loss of generality that

$f(Y_T) \to f(Y)$ a.s.

so that Fatou's lemma indicate $\mathbb{E}\big[|f(Y)| \big] \leq \liminf_{T \to +\infty} \underbrace{\mathbb{E}\big[|f(Y_T)| \big]}_{< +\infty}$

It only remains to prove (2): $\mathbb{E}\left[\max_{k\le N} G_k\right] \sim \sqrt{2\ln N}$

where G_j iid $\sim \mathcal{N}(0,1)$

* Easy (and useless part for our proof): $\mathbb{E}\left[\max_{k\le N} G_k\right] \leqslant \sqrt{2\ln N}$

Lemma: If $V_1, \dots V_N$ are such that $\mathbb{E}\left[e^{\lambda V_j}\right] \le e^{\lambda^2\sigma^2/2}$ $\forall j$ $\forall \lambda > 0$

then $\mathbb{E}\left[\max_{k\le N} V_k\right] \leqslant \sqrt{2\sigma^2 \ln N}$

Note: Valid even without independence $\rightarrow$ independence will be needed for the lower bound

If $G_k \sim \mathcal{N}(0,\sigma^2)$ then $\mathbb{E}\left[e^{\lambda G_k}\right] = e^{\lambda^2\sigma^2/2}$

If $G_k \in [m, M]$ with $\mathbb{E}[G_k] = 0$ then (Hoeffding's lemma) $\mathbb{E}\left[e^{\lambda G_k}\right] \le e^{\lambda^2 (M-m)^2/8}$

↳ We call subgaussian the random variables V_k satisfying the assumptions of the lemma.

Proof: Pisier's argument:

$$\mathbb{E}\left[\max_{k\le N} V_k\right] \overset{\substack{\text{Jensen's ineq.} \\ \forall \lambda > 0}}{\leqslant} \frac{1}{\lambda} \ln \mathbb{E}\left[e^{\lambda \max_{k\le N} V_k}\right]$$

$$\leqslant \frac{1}{\lambda} \ln \mathbb{E}\left[\sum_{k=1}^{N} e^{\lambda V_k}\right] \leqslant \frac{1}{\lambda} \ln\left(N e^{\lambda^2\sigma^2/2}\right)$$

$$= \frac{\ln N}{\lambda} + \lambda \frac{\sigma^2}{2} = \sqrt{2\sigma^2 \ln N}$$

choose $\lambda^* = \sqrt{\dfrac{2\ln N}{\sigma^2}}$

* « Difficult » part of the proof: $\liminf_{N\to+\infty} \dfrac{\mathbb{E}\left[\max_{k\le N} G_k\right]}{\sqrt{2\ln N}} \geqslant 1$

(Credit: Pascal Massart explained to me how to proceed efficiently!)

We use: let $F_N = \Phi^N$ be the cumulative distribution function of $\max_{k\le N} G_k$, where Φ is the cumulative distribution function of the $\mathcal{N}(0,1)$ distribution.

F_N is a bijection $\mathbb{R} \to (0,1)$ so that, for $U \sim \mathcal{U}_{[0,1]}$,

$F_N^{-1}(U) = \Phi^{-1}(U^{1/N})$ and $\max_{k \leq N} G_k$ have the same distribution.

In particular,

$$\mathbb{E}\Big[\max_{k\leq N} G_k\Big] = \mathbb{E}\big[\Phi^{-1}(U^{1/N})\big] = \int_0^1 \Phi^{-1}(u^{1/N})\,du$$

we separate the integrals depending on the sign of the integrand.

$$= \underbrace{\int_0^{1/2^N} \underbrace{\Phi^{-1}(u^{1/N})}_{\leq 0}\,du}_{\mathbb{E}\left[\max_{k\leq N} G_k \, \mathbb{1}_{\{\max_{k\leq N} G_k \leq 0\}}\right]} + \int_{1/2^N}^1 \underbrace{\Phi^{-1}(u^{1/N})}_{\geq 0}\,du$$

$\mathbb{E}\Big[\max_{k\leq N} G_k \, \mathbb{1}_{\{\max_{k\leq N} G_k \leq 0\}}\Big]$ is ≤ 0 and is

$$\geq \mathbb{E}\Big[G_1 \, \mathbb{1}_{\{\max_{k\leq N} G_k \leq 0\}}\Big] = \mathbb{E}\Big[G_1 \, \mathbb{1}_{\{G_1 \leq 0\}} \, \mathbb{1}_{\{\max_{k\leq N} G_k \leq 0\}}\Big] \geq \mathbb{E}\Big[G_1 \, \mathbb{1}_{\{G_1 \leq 0\}}\Big]$$

Thus

$$\Big|\mathbb{E}\Big[\max_{k\leq N} G_k \, \mathbb{1}_{\{\max_{k\leq N} G_k \leq 0\}}\Big]\Big| \leq \Big|\mathbb{E}\big[G_1 \, \mathbb{1}_{\{G_1 \leq 0\}}\big]\Big| \underset{\text{Cauchy-Schwarz}}{\leq} \sqrt{\mathbb{E} G_1^2}\,\sqrt{\mathbb{P}\{G_1 \leq 0\}} = 1/\sqrt{2}$$

fix any $\delta > 0$; for N large enough, $\delta \geq 1/2^N$

$$\int_{1/2^N}^1 \Phi^{-1}(u^{1/N})\,du \geq \int_\delta^1 \Phi^{-1}(u^{1/N})\,du \geq (1-\delta)\,\Phi^{-1}(\delta^{1/N})$$

as Φ^{-1} increasing

Thus we have proved so far:

$$\liminf_{N\to+\infty} \frac{\mathbb{E}\left[\max_{k\leq N} G_k\right]}{\sqrt{2\ln N}} \geq \sup_{\delta\in(0,1)} \liminf_{N\to+\infty} \frac{(1-\delta)\,\Phi^{-1}(\delta^{1/N})}{\sqrt{2\ln N}}$$

It's only a matter of real analysis / calculus now:

We will successfully prove

(a) $1-\Phi(x) \underset{x\to+\infty}{\sim} e^{-x^2/2} \big/ x\sqrt{2\pi}$

(b) $\ln \dfrac{1}{1-v} \sim \left(\Phi^{-1}(v)\right)^2/2$ as $v \nearrow 1$

(c) thus the desired result.

Proof of (a): by two integration by parts (IbP)

$$1-\Phi(x) = \frac{1}{\sqrt{2\pi}}\int_x^{+\infty} e^{-t^2/2}\,dt = \frac{1}{\sqrt{2\pi}}\int_x^{+\infty} t e^{-t^2/2}\cdot\frac{1}{t}\,dt$$

$$\underset{\substack{\text{first}\\ \text{IbP}}}{=} \underbrace{\left[-\frac{1}{\sqrt{2\pi}}\frac{e^{-t^2/2}}{t}\right]_x^{+\infty}}_{= \frac{e^{-x^2/2}}{x\sqrt{2\pi}}} - \underbrace{\frac{1}{\sqrt{2\pi}}\int_x^{+\infty}\frac{e^{-t^2/2}}{t^2}\,dt}$$

Second IbP:
$$0 \leqslant \frac{1}{\sqrt{2\pi}}\int_x^{+\infty} t e^{-t^2/2}\,\frac{1}{t^3}\,dt$$

$$= \left[-\frac{1}{\sqrt{2\pi}}\frac{e^{-t^2/2}}{t^3}\right]_x^{+\infty} - \underbrace{\int_x^{+\infty}}_{\geqslant 0}$$

$$\text{thus } \leqslant \frac{1}{\sqrt{2\pi}}\frac{e^{-x^2/2}}{x^3}$$

so that the $e^{-x^2/2}/x\sqrt{2\pi}$ term was dominating in what the first IbP yielded, hence the result.

Proof of (b): Recall that if $f(x) \sim g(x)$ and $\ln f(x)$ is bounded away from 0 in the limit, then $\ln f(x) \sim \ln g(x)$

indeed: $$\frac{\ln g(x)}{\ln f(x)} = 1 + \frac{\ln\left(g(x)/f(x)\right)}{\ln f(x)} \longrightarrow 1$$

In particular

$$\ln \frac{1}{1-\Phi(x)} \underset{x\to+\infty}{\sim} \ln\left(e^{x^2/2}\, x\sqrt{2\pi}\right) \underset{x\to+\infty}{\sim} \frac{x^2}{2}$$

With $x = \Phi^{-1}(v) \longrightarrow +\infty$ as $v \to 1$ (by composing limits):

$$\ln \frac{1}{1-v} \underset{v\to 1}{\sim} \left(\Phi^{-1}(v)\right)^2 / 2$$

(c) $\Phi^{-1}(\delta^{1/N}) \sim \sqrt{2 \ln \frac{1}{1-\delta^{1/N}}}$ given $\delta^{1/N} \xrightarrow{<} 1$ as $N \to +\infty$

$\sim \sqrt{2 \ln N}$ as $N \to +\infty$ given $1-\delta^{1/N} = 1 - \exp\left(\frac{1}{N}\ln\delta\right) \sim -\frac{1}{N}\ln\delta = \frac{1}{N}\ln\frac{1}{\delta}$

thus :

$$\liminf_{N} \frac{\mathbb{E}\left[\max_{k\leq N} G_k\right]}{\sqrt{2\ln N}} \geqslant \sup_{\delta\in(0,1)} \left\{ (1-\delta) \times \underbrace{\liminf_{N\to+\infty} \frac{\Phi^{-1}(\delta^{1/N})}{\sqrt{2\ln N}}}_{=1} \right\} = 1$$

Exercice Finite-time lower bound. (also known as: Non-asymptotic lower bound)

It's a difficult exercise, try to do as much as possible! Part of the difficulty comes from the manipulation of Kullback-Leibler divergences, we will study their properties in detail in a few weeks when studying the lower bounds for stochastic bandits.

Let $\mathbb{P}_0$ be a probability such that the losses L_{kt} are iid $\sim \mathcal{B}(1/2)$ $\forall k, t$

For $j \in \{1, \dots N\}$ let $\mathbb{P}_j$ be a probability such that:

- all losses L_{kt} are independent
- $L_{kt} \sim Ber(1/2)$ $\forall t$, $\forall k \neq j$
- $L_{jt} \sim Ber(1/2 - \varepsilon)$ $\forall t$

(i) Show that

$$\sup_{\ell_{jt} \in [0,1]} \left\{ \sum_{j,t} p_{jt} \ell_{jt} - \min_k \sum_{t=1}^T \ell_{kt} \right\} \geq T\varepsilon \max_{k=1,\dots N} \left\{ 1 - \frac{1}{T} \sum_{t=1}^T \mathbb{E}_k [p_{kt}] \right\}$$

REMINDER or QUICK INTRODUCTION TO A NEW OBJECT:

Recall that the Kullback-Leibler divergence between two probability distributions μ and ν equals:

$$KL(\nu, \mu) = \begin{cases} +\infty & \text{if } \mu \text{ not absolutely continuous wrt } \nu \\ \int \left(\frac{d\nu}{d\mu} \ln \frac{d\nu}{d\mu} \right) d\mu & \in [0, +\infty] \end{cases}$$

$$= \int \left(\ln \frac{d\nu}{d\mu} \right) d\nu \quad \text{if } \nu \ll \mu$$

(KL well-defined as $x \mapsto x \ln x$ is $\geq -1/e$ over $(0, +\infty)$)

KL has the following properties:

- $KL(\nu \otimes \nu', \mu \otimes \mu') = KL(\nu, \mu) + KL(\nu', \mu')$ ⟸ by Fubini-Tonelli
- $\forall$ random variable X, $KL(\nu^X, \mu^X) \leq KL(\nu, \mu)$ ⟸ data compression inequality (we take it for granted and will prove it later)

We denote by $kl(p,q) = KL(Ber(p), Ber(q))$

$$= p \ln \frac{p}{q} + (1-p) \ln \frac{1-p}{1-q}$$ the KL-divergence between two Bernoulli distributions.

 Lecture 2 — Winter 2019 term Lecture 2 — Winter 2019 term

2) Prove FANO's lemma as revisited by Lucien Birgé:

let $(\Omega, \mathcal{F})$ be a measurable space

let $Q_1, \dots Q_N$ be probability distributions over Ω

let $(A_1, \dots A_N)$ be a partition of Ω

then

$$\min_{j=1\dots N} Q_j(A_j) \leqslant \max\left\{ \frac{2e}{2e+1}, \frac{\overline{K}}{\ln N} \right\}$$

where $\overline{K} = \dfrac{1}{N-1} \displaystyle\sum_{j=2}^{N} KL(Q_j, Q_1)$

Consider $p = \dfrac{1}{N-1} \displaystyle\sum_{j=2}^{N} Q_j(A_j)$ and $q = \dfrac{1}{N-1} \displaystyle\sum_{j=2}^{N} Q_1(A_j)$

and denote $a = \min_{j=1..N} Q_j(A_j)$. Show that:

- $kl(p,q) \leqslant \overline{K}$ / to that end, first prove that KL is jointly convex (it is a consequence of the data-processing inequality, explain why)
- $kl(p,q)/\ln N \geqslant a$ for $a \geqslant 2e/2e+1$

(3) Extend FANO's lemma to random variables so as to show

$$\min_{k=1,\dots N} \mathbb{E}_k\left[\frac{1}{T} \sum_{t=1}^{T} p_{kt} \right] \leqslant \max\left\{ \frac{2e}{2e+1}, \frac{\overline{K}'}{\ln N} \right\}$$

where $\overline{K}' = \dfrac{1}{N-1} \displaystyle\sum_{j=2}^{N} KL\left(\mathbb{P}_j^L, \mathbb{P}_1^L\right)$ with $L = (L_{kt})_{\substack{t \leqslant T \\ k \leqslant N}}$.

(4) Show that $\overline{K}' \leqslant 5T\varepsilon^2$ for $\varepsilon \leqslant 1/10$.

(5) Conclude to the following theorem:

Theorem: For all strategies, for all $N \geqslant 2$ and $T \geqslant 17 \ln N$,

$$\sup R_T \geqslant 0.06 \sqrt{T \ln N}$$