

THE PROOF OF $0 \leq x \leq \mu \Rightarrow P\left(\frac{S_m}{n} \leq x\right) \approx e^{-n \cdot I(x)}$

IS SIMILAR AND WE OMIT IT.

NOW X_1, X_2, \dots ARE GENERAL I.I.D. R.V.'S

IF $\mu = E(X_i)$ THEN $\forall x > \mu$ WE HAVE

$\lim_{n \rightarrow \infty} P\left(\frac{S_m}{n} \geq x\right) = 0$ BY WEAK LAW OF LARGE NUMBERS.

BUT NOW FAST DOES IT CONVERGE TO ZERO?

DEF: $\lambda \in \mathbb{R} : Z(\lambda) := E(e^{\lambda \cdot X_i})$

THE MOMENT GENERATING FUNCTION OF X_i

LET $\hat{I}(\lambda) := \ln(Z(\lambda))$

THE LOGARITHMIC MOMENT GEN. FUNCTION OF X_i

NOTE: $E(e^{\lambda S_m}) = E(e^{\lambda X_1} \cdot e^{\lambda X_2} \cdot \dots \cdot e^{\lambda X_m}) =$

$= E(e^{\lambda X_1}) \cdot E(e^{\lambda X_2}) \cdot \dots \cdot E(e^{\lambda X_m}) = (Z(\lambda))^m$

↑ THE EXPECTED VALUE OF THE PRODUCT OF INDEPENDENT R.V.'S IS EQUAL TO THE PRODUCT OF THEIR EXPECTATIONS.

NOW FOR ANY $\lambda \geq 0$:

MARKOV'S INEQUALITY

$$P\left(\frac{S_m}{n} \geq x\right) = P\left(e^{\lambda \cdot S_m} \geq e^{\lambda \cdot n \cdot x}\right) \leq$$

$$\frac{E\left(e^{\lambda \cdot S_m}\right)}{e^{\lambda \cdot n \cdot x}} = \frac{(Z(\lambda))^m}{e^{\lambda \cdot n \cdot x}} = e^{m \cdot (\hat{I}(\lambda) - \lambda \cdot x)}$$

NOW CHOOSE λ THAT GIVES THE BEST BOUND!

IF $X_i \sim \text{BER}(p)$ THEN $Z(\lambda) = p \cdot e^{\lambda \cdot 1} + (1-p) \cdot e^{\lambda \cdot 0}$

THUS $\hat{I}(\lambda) = \ln((1-p) + p \cdot e^\lambda)$

$\Psi(\lambda)$

GIVEN $x \geq E(X_i) = p$, WHAT IS $\min_{\lambda \geq 0} (\hat{I}(\lambda) - \lambda \cdot x)$?

$$\Psi'(\lambda) = \hat{I}'(\lambda) - x = \frac{p \cdot e^\lambda}{(1-p) + p \cdot e^\lambda} - x \stackrel{!}{=} 0 \quad \text{WANT}$$

$$\Psi'(\lambda^*) = 0 \quad \text{IF} \quad \lambda^* := \ln\left(\frac{x}{1-x} \cdot \frac{1-p}{p}\right) \quad \text{PLUGGING THIS BACK INTO } \Psi:$$

$$\Psi(\lambda^*) = \ln((1-p) + p \cdot e^{\lambda^*}) - \lambda^* \cdot x = (1-x) \cdot \ln\left(\frac{1-p}{1-x}\right) + x \cdot \ln\left(\frac{p}{x}\right) = -I(x) \quad \text{SEE PAGE 2}$$

THUS $P\left(\frac{S_m}{n} \geq x\right) \leq e^{-n \cdot I(x)}$

THIS IS GOOD NEWS!

OUR NEW METHOD GAVE ...

OUR NEW METHOD GAVE THE OPTIMAL UPPER BOUND ON $P\left(\frac{S_m}{n} \geq x\right)$ IN THE CASE OF $X_i \sim \text{BER}(p)$, SO MAYBE IT IS ALSO OPTIMAL IN THE CASE OF GENERAL I.I.D. $X_{1,1}, X_{1,2}, \dots$

BACK TO THE GENERAL CASE: WE HAVE SHOWN THAT IF $S_m = X_{1,1} + \dots + X_{1,m}$ AND $x > E(X_i)$ THEN $P\left(\frac{S_m}{n} \geq x\right) \leq e^{-n \cdot I(x)}$

WHERE $I(x) := \max_{\lambda \geq 0} (\lambda x - \hat{I}(\lambda))$ $\hat{I}(\lambda) = \ln(z(\lambda))$
 $z(\lambda) = E(e^{\lambda X_i})$

DEF: $f: \mathbb{R} \rightarrow \mathbb{R} \cup \{+\infty\}$, LET US DEFINE

$\hat{f}(\lambda) = \sup_{x \in \mathbb{R}} \{ \lambda \cdot x - f(x) \}$ FOR ANY $\lambda \in \mathbb{R}$
 (NOTE: $\hat{f}: \mathbb{R} \rightarrow \mathbb{R} \cup \{+\infty\}$)

\hat{f} IS THE LEGENDRE TRANSFORM OF f

WE WILL NOW LEARN ABOUT THE PROPERTIES OF $f \mapsto \hat{f}$

CLAIM: \hat{f} IS A CONVEX FUNCTION

PROOF: FOR ANY FIXED $x \in \mathbb{R}$ THE FUNCTION

$\lambda \mapsto \lambda \cdot x - f(x)$ IS AN AFFINE LINEAR FUNCTION,

THUS \hat{f} IS THE SUPREMUM OF " - 'S,

HENCE IT IS CONVEX. ✓

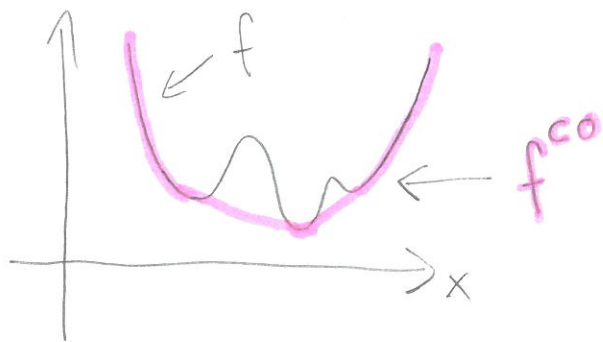
DEF: THE LOWER CONVEX ENVELOPE f^{co}

OF A FUNCTION f IS THE SUPREMUM OF

THOSE AFFINE LINEAR FUNCTIONS THAT LIE

BELOW f :

$$f^{co}(x) = \sup \{ g(x) : g(y) = a \cdot y + b, \forall y, g(y) \leq f(y) \}$$



FACT: IF f IS CONVEX AND CONTINUOUS,

THEN $f \equiv f^{co}$



CLAIM: IF $f \leq g$ THEN $\hat{g} \leq \hat{f}$ 

PROOF: $\forall x \forall \lambda : \lambda \cdot x - f(x) \geq \lambda \cdot x - g(x)$, THUS

$$\hat{f}(\lambda) = \sup_x \{ \lambda x - f(x) \} \geq \sup_x \{ \lambda x - g(x) \} = \hat{g}(\lambda)$$

CLAIM:

$$\hat{\hat{f}} \leq f^{co}$$

THE LEGENDRE TRANSFORM OF THE LEGENDRE TRANSFORM OF f

LIES BELOW THE LOWER CONVEX ENVELOPE OF f .

PROOF: ENOUGH TO SHOW THAT

$$\hat{\hat{f}} \leq f$$

SINCE $\hat{\hat{f}}$ IS THE SUPREMUM OF SOME AFFINE LINEAR FUNCTIONS THAT LIE BELOW f BY \star ,

BUT f^{co} IS THE SUP. OF ALL AFF. LIN.

FUNCTIONS THAT LIE BELOW f , SO $\hat{\hat{f}} \leq f^{co}$.

NOW WE SHOW \star :

$$\forall \lambda \forall x \hat{f}(\lambda) = \sup_x \{ \lambda x - f(x) \}, \text{ so}$$

$$\forall \lambda \forall x \hat{f}(\lambda) \geq \lambda x - f(x), \text{ so}$$

$$\forall \lambda \forall x f(x) \geq \lambda x - \hat{f}(\lambda), \text{ so}$$

$$\forall x f(x) \geq \sup_{\lambda} \{ \lambda x - \hat{f}(\lambda) \} = \hat{\hat{f}}(x)$$

CLAIM: ACTUALLY WE HAVE

$$\hat{\hat{f}} = f^{co}$$

(THUS, IN PARTICULAR, IF f IS CONVEX AND CONTINUOUS, THEN

$$\hat{\hat{f}} = f$$

PROOF: FIRST NOTE THAT IF $g(x) = ax + b$

THEN $\hat{\hat{g}} = g$. INDEED:

$$\hat{g}(\lambda) = \sup_x \{ \lambda x - ax - b \} = \begin{cases} +\infty & \text{IF } \lambda \neq a \\ -b & \text{IF } \lambda = a \end{cases}$$

$$\hat{\hat{g}}(x) = \sup_{\lambda} \{ \lambda x - \hat{g}(\lambda) \} = ax - \hat{g}(a) = ax + b = g(x)$$

NOW IN THE CASE OF GENERAL f , WE ONLY NEED TO SHOW $\hat{\hat{f}} \geq f^{co}$. ENOUGH

TO SHOW THAT IF $g(x) = ax + b$ AND $g \leq f$

THEN $g \leq \hat{\hat{f}}$. AND INDEED:

$$\boxed{g \leq f} \Rightarrow \boxed{\hat{g} \geq \hat{f}} \Rightarrow \boxed{\hat{\hat{g}} \leq \hat{\hat{f}}} \quad \text{BUT } \hat{\hat{g}} = g \quad \checkmark$$

CLAIM: IF f'' IS POSITIVE AND CONTINUOUS,

THEN $\hat{f}'^B = (f')^{-1}$ AND

$$\hat{f}^A(x) = x \cdot (f')^{-1}(x) - f((f')^{-1}(x))$$

PROOF: $\hat{f}(x) = \sup_{\lambda} \{ \lambda x - f(\lambda) \}$

GIVEN x , LET $\psi(\lambda) = \lambda x - f(\lambda)$

THEN ψ IS STRICTLY CONCAVE, SO TO MAXIMIZE IT, WE NEED TO FIND THE UNIQUE λ^* FOR WHICH $\psi'(\lambda^*) = 0$.

$\psi'(\lambda) = x - f'(\lambda)$, THUS WANT: $f'(\lambda^*) = x$,

THUS $\lambda^* = (f')^{-1}(x)$ AND THUS

$\hat{f}(x) = \psi(\lambda^*) = \lambda^* \cdot x - f(\lambda^*) = x \cdot (f')^{-1}(x) - f((f')^{-1}(x))$

NOW $\frac{d}{dx} (f')^{-1}(x) = \frac{1}{f''(\lambda^*)}$, SO

$\hat{f}'(x) = \lambda^* + x \cdot \frac{1}{f''(\lambda^*)} - \underbrace{f'(\lambda^*)}_x \cdot \frac{1}{f''(\lambda^*)} = \lambda^* = (f')^{-1}(x)$

NOW LET US CHECK FOR FUN THAT $\hat{\hat{f}} = f$

$\hat{\hat{f}}(\lambda) = \lambda \cdot (\hat{f}')^{-1}(\lambda) - \hat{f}((\hat{f}')^{-1}(\lambda))$

$\lambda \cdot f'(\lambda) - \hat{f}(f'(\lambda))$

$\lambda \cdot f'(\lambda) - \left(\underbrace{f'(\lambda)}_{\lambda} \cdot \underbrace{(f')^{-1}(f'(\lambda))}_{f(\lambda)} - f((f')^{-1}(f'(\lambda))) \right) = f(\lambda)$