

Review

- data compression
 $\begin{cases} \text{zero-error} \\ \text{variable-length} \\ \text{fixed-length} \end{cases}$
- neither zero-error nor non-zero error
 - $x=0$ or $x \neq 0$
 - $x_n \neq 0, \forall n$ $x_n \rightarrow 0$ as $n \rightarrow \infty$
tends to
- Def. A codeword symbols per source symbol R is **achievable** if there exists a sequence of (fixed-length) codes $\mathcal{C}_k$ s.t.

$$R_k \rightarrow R \quad \text{and}$$

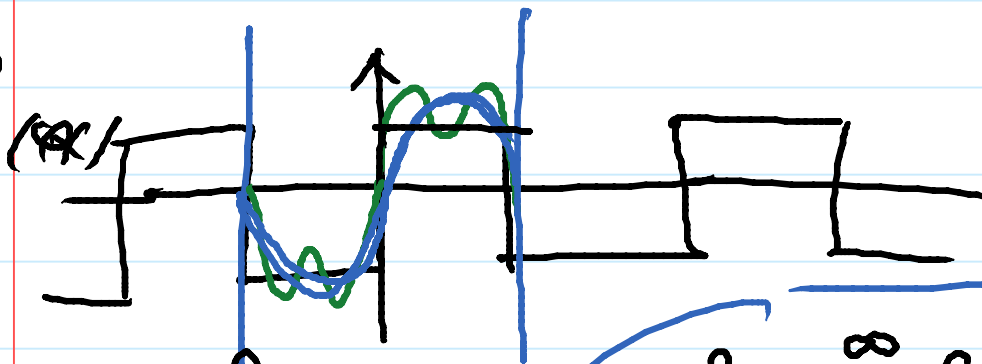
$$P_{e,k} \rightarrow 0$$

Start from what you know.
the simplest. $\leftarrow$ Simplify!

discrete optimization $\mathbb{R}^n \rightarrow \mathbb{R}$
(continuous) optimization $(\mathbb{R}^n) \rightarrow \mathbb{R}$
mixed "

convergence of a sequence of $\left\{ \begin{array}{l} \text{(i) real numbers} \\ \text{(ii) real functions} \\ \text{(iii) random variables.} \end{array} \right.$
measurable

(ii)



uniform
 $\Downarrow$
everywhere

$\Downarrow$
almost everywhere

$\Downarrow$
in measure

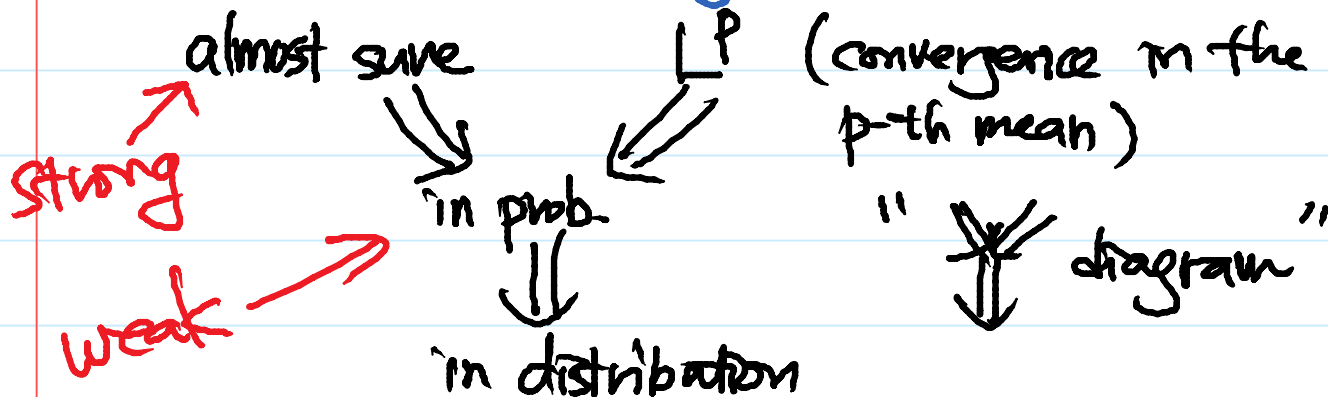
$$f(x) = \sum_{n=1}^{\infty} f_n(x)$$

$$\int_a^b f(x) dx \stackrel{?}{=} \sum_{n=1}^{\infty} \int_a^b f_n(x) dx$$

L^p convergence

(iii) Convergence of a sequence of random variables

4 modes of convergence



Convergence in probability

Def. Given a probability space $(\Omega, \mathcal{F}, P)$, a sequence of random variables X_n converges to a random variable X in probability

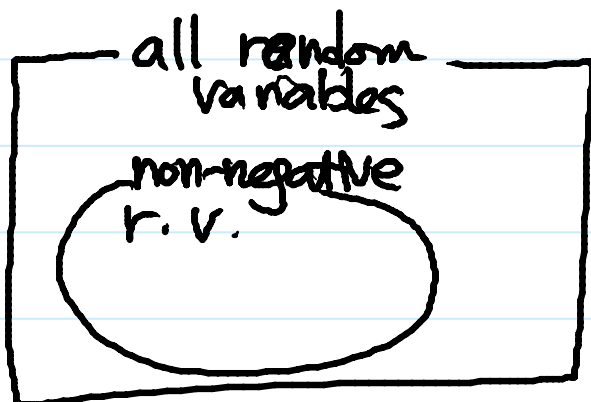
if $\forall \epsilon > 0 \quad P(|X_n - X| > \epsilon) \rightarrow 0$ as $n \rightarrow \infty$.

$$a) \quad P(\{\omega : |X_n(\omega) - X(\omega)| > \epsilon\}) \rightarrow 0$$

Notation $X_n \xrightarrow{P} X$ or $X_n \rightarrow X \text{ P.}$

- Markov's inequality
Chebyshev's "
WLLN

- The Markov Inequality

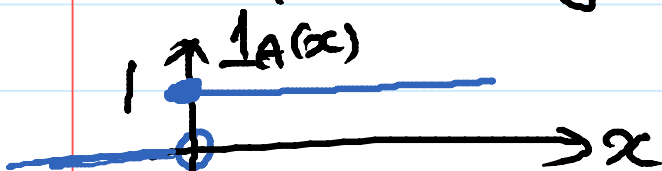


Def. A random variable X is non-negative if $\Pr(X \geq 0) = 1$

(MI) If X is non-negative, then $\Pr(X > a) \leq \frac{E\{X\}}{a}$ where $a > 0$ is a const.

- Indicator function $1_A(x) \triangleq \begin{cases} 1, & \text{if } x \in A \\ 0, & \text{if } x \notin A. \end{cases}$

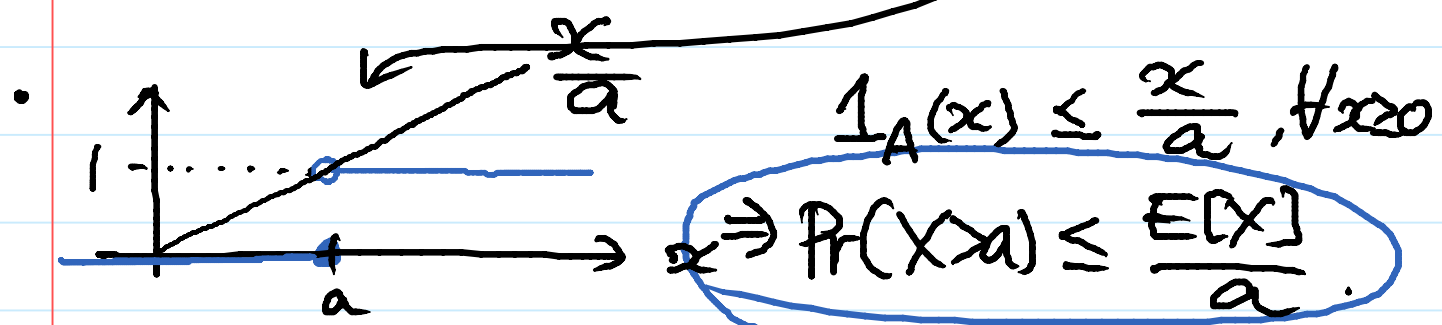
$$A = \{y \in \mathbb{R} : y \geq 0\}$$



$$\begin{aligned}
 \bullet \quad \Pr(X \in A) &= E\{1_A(X)\} \\
 &= \sum_{x \in \Omega} 1_A(x) \Pr(X=x) \\
 &= \sum_{x \in A} \Pr(X=x) \\
 &= \Pr(X \in A)
 \end{aligned}$$

$$\Pr(X > a) = E\left\{ \underbrace{1_{\{x \in \mathbb{R} : x > a\}}(x)} \right\}$$

$$\begin{aligned}
 \bullet \quad f_1(x) &\geq f_2(x), \quad x \in A \text{ and } \\
 \Pr(X \in A) &= 1 \\
 \Rightarrow E[f_1(X)] &\geq E[f_2(X)]
 \end{aligned}$$



$$\bullet \quad \text{The Chebyshev Inequality} \\
 \Pr(|X - \bar{X}| > k\sigma) \leq \frac{1}{k^2}$$

(proof)

$$= \Pr((X - \bar{X})^2 > k^2 \sigma^2) \leq \frac{E(X - \bar{X})^2}{k^2 \sigma^2} = \frac{1}{k^2}$$

page 05

2013년 5월 20일 수요일

오후 10:49

The Weak Law of Large Numbers Theorem

Given a sequence of uncorrelated r.v.'s X_n with $E[X_n] = \mu$ and $\text{Var}[X_n] = \sigma^2 < \infty$, the sequence of random variables $(Y_n)_{n=1}^{\infty}$ satisfies

$$Y_n \rightarrow \mu \text{ in prob.}$$

If

$$Y_n \triangleq \frac{1}{n} (X_1 + X_2 + \dots + X_n).$$

2 sequences

$$\begin{pmatrix} X_1 & X_2 & X_3 & \dots \\ Y_1 & Y_2 & Y_3 & \dots \end{pmatrix}$$

(proof)

To show

$$\forall \varepsilon > 0, \Pr(|Y_n - \mu| > \varepsilon) \rightarrow 0 \text{ as } n \rightarrow \infty.$$
$$\Pr\left(\left|\frac{X_1 + X_2 + \dots + X_n}{n} - \frac{n\mu}{n}\right| > \varepsilon\right)$$

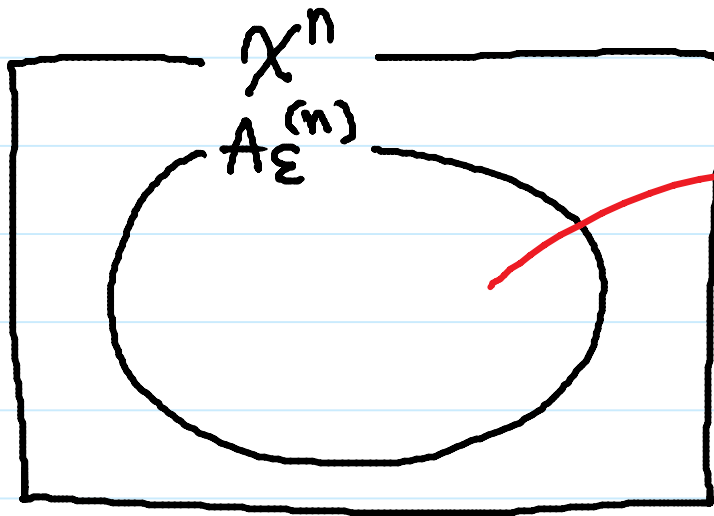
$$= \Pr\left(\left|\frac{1}{n} \sum_{i=1}^n (X_i - \mu)\right| > \varepsilon\right)$$

$$\leq \frac{E\left\{\frac{1}{n^2} \left(\sum_{i=1}^n (X_i - \mu)\right)^2\right\}}{\varepsilon^2} = \frac{\sum_{i=1}^n E\{(X_i - \mu)^2\}}{n^2 \varepsilon^2} = \frac{\sigma^2}{n \varepsilon^2}$$

(WLLN) $\frac{X_1 + X_2 + \dots + X_n}{n} \rightarrow E\{X_i\}$ in prob.

$$(WLLN) \quad \frac{X_1 + X_2 + \dots + X_n}{n} \rightarrow E\{X_i\} \text{ in prob.}$$

Preview



$$\begin{aligned} & \left[\begin{aligned} & \Pr(\underline{X}^{(n)} \notin A_{\epsilon}^{(n)}) \\ & < \epsilon^{(n)} \\ & |A_{\epsilon}^{(n)}| < |X^n| \end{aligned} \right] \\ & \text{WLLN } \delta \end{aligned}$$