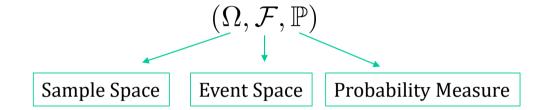
LEC017 Review of Probability I

VG441 SS2020

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Probability Space

Probability space as a triplet



A coin toss

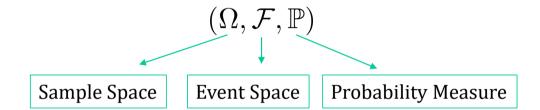
$$\Omega = \{H, T\}$$

$$\mathcal{F} = 2^{\Omega} = \{\emptyset, \{H\}, \{T\}, \Omega\}$$

$$\mathbb{P} : \mathcal{F} \to [0, 1]$$

Probability Axioms

Probability space as a triplet



• 3 Axioms

$$\mathbb{P}(\Omega) = 1$$

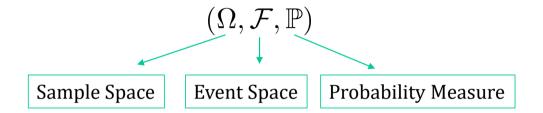
If
$$A \in \mathcal{F}$$
, then $0 \leq \mathbb{P}(A) \leq 1$

If $A_1, A_2, \ldots \in \mathcal{F}$ and disjoint, then $\mathbb{P}(A_1 \cup A_2 \cup \ldots) = \mathbb{P}(A_1) + \mathbb{P}(A_2) + \ldots$



Random Variable (RV)

A convenient representation of sample space



Random variable

$$X:\Omega\to\mathbb{R}$$

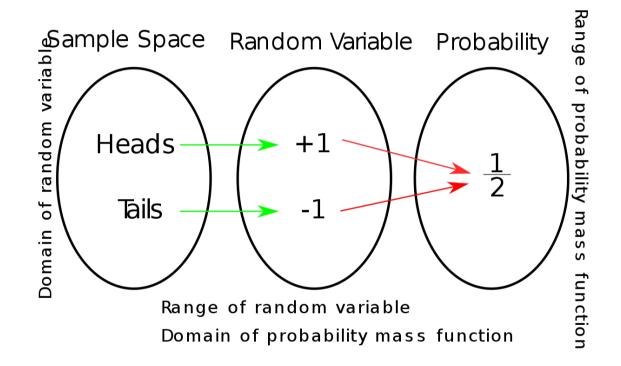
Coin toss

$$X = \begin{cases} 0 & \text{if T} \\ 1 & \text{if H} \end{cases}$$

Assign probability measure or distribution...

$$\mathbb{P}(X=1) = p, \quad \mathbb{P}(X=0) = 1 - p$$

A Fair Coin Toss (as Bernoulli(p=1/2))



Common Random Variable (RV)

Discrete (PMF, CDF, MGF)

- Bernoulli
- Binomial
- Poisson
- Geometric
- Negative Binomial
- Hypergeometric
- Dirichlet (multinomial)
-

Continuous (PDF, CDF, MGF)

- Uniform
- Normal
- Exponential
- Beta
- Gamma
- Weibull
- Gumbel (extreme value)
-

PDF, CDF, Expectation, Moment, MGF

- Probability mass function (discrete) $\mathbb{P}(X=x)$
- Probability density function (continuous)

$$f(x) \approx \frac{1}{\delta} \mathbb{P}(x \le X \le x + \delta)$$

- Cumulative distribution function $F(x) = \mathbb{P}(X \leq x)$
- Expectation $\mathbb{E}(X)$
- Variance Var(X)
- Covariance Cov(X, Y)
- Correlation Coefficient $ho_{X,Y}$ $\rho_{X,Y}$ $\rho_{X,Y}$
- Moment generating function $M(\theta) = \mathbb{E}(e^{\theta X})$

$$M_X(t) = \int_{-\infty}^{\infty} e^{tx} f(x) dx$$

= $\int_{-\infty}^{\infty} \left(1 + tx + \frac{t^2 x^2}{2!} + \dots + \frac{t^n x^n}{n!} + \dots \right) f(x) dx$
= $1 + tm_1 + \frac{t^2 m_2}{2!} + \dots + \frac{t^n m_n}{n!} + \dots,$

Conditional Probability

Conditional probability

$$\mathbb{P}(A \mid B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}$$

• Bayes Theorem (A_i disjoint cases)

$$P(A_i \mid B) = \frac{P(B \cap A_i)}{P(B)} = \frac{P(B \mid A_i) P(A_i)}{P(B)} = \frac{P(B \mid A_i) P(A_i)}{\sum_{j=1}^{n} P(B \mid A_j) P(A_j)}$$

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Conditional Probability

Conditional probability

$$\mathbb{P}(A \mid B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}$$

Bayes Theorem (A_i disjoint cases)

$$P(A_i | B) = \frac{P(B | A_i) P(A_i)}{P(B)} = \frac{P(B | A_i) P(A_i)}{\sum_{j=1}^{n} P(B | A_j) P(A_j)}$$

- What is the probability of a customer coming from Copenhagen spends above the median of the rest of the customers, on some item? Facts:
 - People from Copenhagen spent 19.5%, people from Hongkong spent 7.8% and the rest (of the world) spent 72.7%.
 - 48.4% of people from Copenhagen spent above the median
 - 35.2% of people from Hongkong spent above the median
 - 56.7% of people from the rest of the world spent above the median

Markov inequality

Let X be a non-negative r.v. Fix a constant a > 0. Then

$$\mathbb{P}(X > a) \le \frac{\mathbb{E}(X)}{a}$$

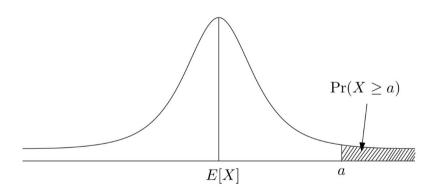


Figure: Markov's Inequality bounds the probability of the shaded region.

Markov inequality

Let X be a non-negative r.v. Fix a constant a > 0. Then $\mathbb{E}(X)$

$$\mathbb{P}(X > a) \le \frac{\mathbb{E}(X)}{a}$$

Proof. Define Y by

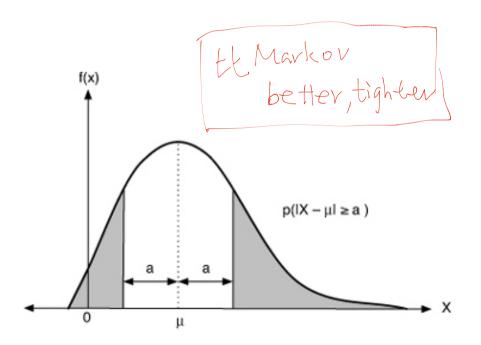
$$Y = \left\{ \begin{array}{ll} a & \text{if } X \geq a \\ 0 & \text{if } X < a \end{array} \right.$$

As $X \geq Y$ a.s., it follows that $\mathbb{E}(X) \geq \mathbb{E}(Y) = a\mathbb{P}(X > a)$.

Chebyshev's inequality

Let X be a r.v. having finite mean μ and variance σ^2 and $\epsilon > 0$ then

$$\mathbb{P}(|X - \mu| \ge \epsilon) \le \frac{\sigma^2}{\epsilon^2}.$$



Chebyshev's inequality

Let X be a r.v. having finite mean μ and variance σ^2 and $\epsilon > 0$ then

$$\mathbb{P}\left(|X - \mu| \ge \epsilon\right) \le \frac{\sigma^2}{\epsilon^2}.$$

Proof. Note that $(X - \mu)^2$ is a non-negative r.v. and

$$\mathbb{P}(|X - \mu| \ge \epsilon) = \mathbb{P}((X - \mu)^2 \ge \epsilon^2) \le \frac{\mathbb{E}(X - \mu)^2}{\epsilon^2} = \frac{\sigma^2}{\epsilon^2}.$$



Convergence of random variables

Convergence in probability

Convergence in probability: $X_n \to X$ i.p. if for all $\epsilon > 0$, we have

$$\mathbb{P}(|X_n - X| \ge \epsilon) \to 0 \text{ as } n \to \infty.$$

Convergence in distribution

Convergence in distribution (or weak convergence): Let X and X_n , $n \in \mathbb{N}$, be random variables with CDFs F and F_n , respectively. We say $X_n \xrightarrow{d} X$ if

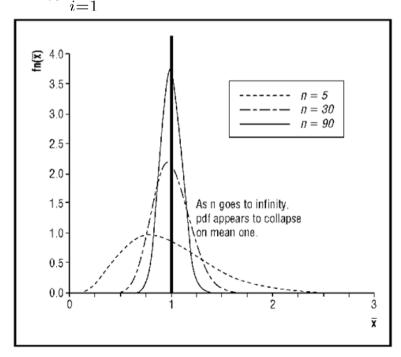
 $\lim_{n\to\infty} F_n(X) = F(x)$, for every $x \in \mathbb{R}$ at which F is continuous.

Suffice to show convergence in MGF, i.e., $M_n(\theta) \ \blacksquare \ M(\theta)$

• (Weak) Law of Large Numbers

Let X_1, \ldots, X_n be i.i.d. having finite mean $\mathbb{E}[X] = \mu$ and variance σ^2 , then

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i \qquad \xrightarrow{i.p.} \qquad \mathbb{E}[X] \quad \text{as } n \to \infty.$$



• (Weak) Law of Large Numbers

Let X_1, \ldots, X_n be i.i.d. having finite mean $\mathbb{E}[X] = \mu$ and variance σ^2 , then

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i \qquad \xrightarrow{i.p.} \qquad \mathbb{E}[X] \quad \text{as } n \to \infty.$$

Proof. Since $\mathbb{E}(\bar{X}_n) = \mu$ and $\mathbf{Var}(\bar{X}_n) = \sigma^2/n$, by Chebyshev's inequality,

$$\mathbb{P}\left(\left|\bar{X}_n - \mu\right| \ge \epsilon\right) \le \frac{\mathbf{Var}(X_n)}{\epsilon^2} = \frac{\sigma^2}{\epsilon^2 n}.$$

Then we drive $n \to \infty$.



Central Limit Theorem

Let $\{X_n\}$ be a sequence of i.i.d. r.v.'s with $\mathbb{E}[X_1] = \mu$ and $\operatorname{Var}(X_1) = \sigma^2 < \infty$. Let $S_n = \sum_{k=1}^n X_k$. Then $\sigma N(0,1)$ as $n \to \infty$. Gaussian samples of size n population sampling distribution distribution of the mean 17

• MGF of $N(\mu, \sigma^2)$

Normal density
$$f\left(x;\mu,\sigma^2\right) = \frac{1}{\sqrt{(2\pi\sigma^2)}}e^{-\frac{1}{2}(x-\mu)^2/\sigma^2}$$

For standard normal Z:

 $=e^{\theta^2/2}$

$$M_{Z}(\theta) = \mathbb{E}\left[e^{\theta Z}\right] = \int_{-\infty}^{\infty} e^{\theta x} f_{Z}(x) dx$$

$$= \int_{-\infty}^{\infty} e^{\theta x} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^{2}}{2}} dx$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(x^{2} - 2x\theta)} dx$$

$$= e^{\theta^{2}/2} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(x - \theta)^{2}} dx$$

$$= pdf \text{ of } \mathcal{N}(\theta, 1)$$

For any normal X:

$$X = \mu + \sigma Z$$

$$M_X(\theta) = \mathbb{E} \left[e^{\theta(\mu + \sigma Z)} \right]$$

$$= e^{\theta \mu} \mathbb{E} \left[e^{\theta \sigma Z} \right]$$

$$= e^{\theta \mu} M_Z(\theta \sigma)$$

$$= e^{\theta \mu} e^{\theta^2 \sigma^2 / 2}$$

$$= e^{(\mu \theta + \frac{\sigma^2 \theta^2}{2})}$$

$$M_X(\theta) - \theta^{\frac{2^2 \theta^2}{2}}$$

• Central Limit Theorem Let $\{X_n\}$ be a sequence of i.i.d. r.v.'s with $\mathbb{E}[X_1] = \mu$ and $\mathbf{Var}(X_1) = \sigma^2 < \infty$.

Let $S_n=\sum_{k=1}^n X_k$. Then $\frac{S_n-n\mu}{\sqrt{n}} \qquad \stackrel{d}{\longrightarrow} \qquad \sigma N(0,1) \quad \text{as} \quad n\to\infty.$ Without loss of

Proof. WLOG, assume
$$\mathbb{E}[X_1] = \mu = 0$$
. It suffices to show that the MGF of S_n/\sqrt{n} converges to that of $Z = N(0, \sigma^2)$. Let $M(\theta) := \mathbb{E}\left[e^{\theta X_1}\right]$. Then we have $M'(0) = \mathbb{E}\left[X_1\right] = 0$ and $M''(0) = \mathbb{E}\left[X_1^2\right] = \sigma^2$. For each $\theta \in \mathbb{R}$,

have
$$M'(0) = \mathbb{E}[X_1] = 0$$
 and $M''(0) = \mathbb{E}[X_1^2] = \sigma^2$. For each $\theta \in \mathbb{R}$,
$$\mathbb{E}\left[e^{\theta \frac{S_n}{\sqrt{n}}}\right] = \left(M\left(\frac{\theta}{\sqrt{n}}\right)\right)^n = \left(1 + \frac{M''(0)}{2} \frac{\theta^2}{n} + o\left(\frac{\theta^2}{n}\right)\right)^n$$

$$= \left(1 + \frac{\sigma^2 \theta^2}{2n} + o\left(\frac{\theta^2}{n}\right)\right)^n \xrightarrow[n \to \infty]{} e^{\frac{\sigma^2 \theta^2}{2}},$$
which is the MGF of $N(0, \sigma^2)$.
$$\text{Which is the MGF of } N(0, \sigma^2).$$