Basics of Probability

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Definition 1 (Probability Space)**.** *A probability space is a triple* $(\Omega, \mathcal{F}, P)$ *where*

- Ω *is the sample space, also called the set of all outcomes.*
- $\mathcal{F}$ *is a* σ*-algebra over* Ω*.* $\mathcal{F}$ *is called the set of all events.*
- $P : \mathcal{F} \mapsto [0, 1]$ *is a measure over* $(\Omega, \mathcal{F})$ *(i.e.,* P *is* σ*-additive) such that* $P(\Omega) = 1$*.* P *is called the probability measure.*

Theorem 1 (Inclusion-Exclusion Principle)**.**

$$\Pr\left(\bigcup_{i=1}^{n} A_i\right) = \sum_{k=1}^{n}(-1)^{k+1} \sum_{1 \le i_1 < \cdots < i_k \le n} \Pr(A_{i_1} \cap \cdots \cap A_{i_k}).$$

Theorem 2. *For randvars* X *and* Y*,* $\operatorname{E}(X + Y) = \operatorname{E}(X) + \operatorname{E}(Y)$*.*

Theorem 3. *For independent randvars* $X_1, \ldots, X_n$*,* $\operatorname{E}(X_1 \ldots X_n) = \operatorname{E}(X_1) \ldots \operatorname{E}(X_n)$*.*

Theorem 4. *For a non-negative randvar* X*,*

$$\operatorname{E}(X) = \begin{cases} \displaystyle\sum_{i=0}^{\infty} \Pr(X > i) & \text{if } X \text{ is discrete} \\ \displaystyle\int_0^{\infty} \Pr(X > x)dx & \text{if } X \text{ is continuous} \end{cases}.$$

Definition 2.

$$\begin{aligned} \operatorname{Cov}(X, Y) &:= \operatorname{E}((X - \operatorname{E}(X))(Y - \operatorname{E}(Y))) = \operatorname{E}(XY) - \operatorname{E}(X)\operatorname{E}(Y) \\ \operatorname{Var}(X) &:= \operatorname{Cov}(X, X) = \operatorname{E}((X - \operatorname{E}(X))^2) = \operatorname{E}(X^2) - \operatorname{E}(X)^2 \end{aligned}$$

Theorem 5.

$$\operatorname{Var}\left(\sum_{i=1}^{n} X_i\right) = \sum_{i=1}^{n} \operatorname{Var}(X_i) + 2 \sum_{1 \le i < j \le n} \operatorname{Cov}(X_i, X_j).$$

Theorem 6. *Let* $\operatorname{MGF}_t(X) := \operatorname{E}(e^{tX})$*. Then* MGF_t *uniquely determines* X*'s CDF.*

Theorem 7 (Change of variables)**.** *Let* $X \in \mathbb{R}^n$ *be a continuous random vector. Let* $g : \mathbb{R}^n \mapsto \mathbb{R}^n$ *be a bijective function having continuous partial derivatives. Then* $f_{g(X)}(y) = f_X(x)|J_g(x)|^{-1}$*, where* $x := g^{-1}(y)$ *and* J_g *is the Jacobian of* g *(i.e.,* $J_g(x)[i, j] := \partial g(x)_i / \partial x_j$*).*

Definition 3. *Let $A = [A_1, A_2, \ldots]$ be an infinite sequence of events. Then*

$$\mathrm{io}(A) = \lim_{m\to\infty} \bigcup_{i=m}^{\infty} A_i = \bigcap_{m=1}^{\infty} \bigcup_{i=m}^{\infty} A_i \qquad \mathrm{ae}(A) = \lim_{m\to\infty} \bigcap_{i=m}^{\infty} A_i = \bigcup_{m=1}^{\infty} \bigcap_{i=m}^{\infty} A_i.$$

$\mathrm{io}(A)$ *are the outcomes in Ω for which infinitely many events in A happen.* $\mathrm{ae}(A)$ *are the outcomes in Ω for which all except finitely many events in A happen.*

Lemma 8 (Borel-Cantelli)**.** $\sum_{i=1}^{\infty} \Pr(A_i) \neq \infty \implies \Pr(\mathrm{io}(A)) = 0$.

Lemma 9. *(Events in A are independent and $\sum_{i=1}^{\infty} \Pr(A_i) = \infty$)* $\implies \Pr(\mathrm{io}(A)) = 1$.

1 Probability Distributions

Table 1: Discrete Probability Distributions

Distribution	$\Pr(X = x)$	$\mathrm{E}(X)$	$\mathrm{Var}(X)$	$\mathrm{MGF}_t(X)$
Bernouilli(p)	$p^x(1-p)^{1-x}$	p	$p(1-p)$	$pe^t + 1 - p$
Binomial(n, p)	$\binom{n}{x} p^x(1-p)^{n-x}$	np	$np(1-p)$	$(pe^t + 1 - p)^n$
Geometric(p)	$(1-p)^{x-1}p$	$1/p$	$(1-p)/p^2$	$\dfrac{pe^t}{1-(1-p)e^t}$
Poisson(λ)	$e^{-\lambda}\lambda^x/x!$	λ	λ	$\exp(\lambda(e^t - 1))$

Table 2: Continuous Probability Distributions

Distribution	$f_X(x)$	$\mathrm{E}(X)$	$\mathrm{Var}(X)$	$\mathrm{MGF}_t(X)$
Uniform(a, b)	$\dfrac{\mathbf{1}(a \le x \le b)}{b-a}$	$\dfrac{a+b}{2}$	$\dfrac{(b-a)^2}{12}$	$\dfrac{e^{bt} - e^{at}}{(b-a)t}$
Exponential(λ)	$\lambda e^{-\lambda x}$	$1/\lambda$	$1/\lambda^2$	$\lambda/(\lambda - t)$
Gamma(n, λ)	$\dfrac{(\lambda x)^{n-1}}{(n-1)!}\lambda e^{-\lambda x}$	n/λ	n/λ^2	$\left(1 - \dfrac{t}{\lambda}\right)^{-n}$
Normal(μ, σ^2)	$\dfrac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$	μ	σ^2	$\exp(\mu t + \sigma^2 t^2/2)$

Theorem 10 (Poisson approximates Binomial)**.** *Let $\lambda \in \mathbb{R}_{\ge 0}$ and $k \in \mathbb{Z}_{\ge 0}$ be constants. Let $X_n \sim \mathrm{Binom}(n, \lambda/n)$. Then $\lim_{n\to\infty} \Pr(X_n = k) = e^{-\lambda}\lambda^k/k!$.*

Theorem 11 (Binomial over Poisson)**.** *Let $N \sim \mathrm{Poisson}(\lambda)$ and $M \mid N \sim \mathrm{Binom}(N, p)$. Then $M \sim \mathrm{Poisson}(\lambda p)$.*

Theorem 12 (Poisson decomposition)**.** *Let $X_1, X_2, \ldots$ be IID randvars, where $\Pr(X_j = i) = p_i$ for $i \in [k]$ and all j, and $\sum_{i=1}^{k} p_i = 1$. Let $N \sim \mathrm{Poisson}(\lambda)$ where $\{N, X_1, X_2, \ldots\}$ is independent. Let $N_i := \sum_{j=1}^{N} \mathbf{1}(X_j = i)$. Then $\{N_1, \ldots, N_k\}$ is independent and $N_i \mid N \sim \mathrm{Binom}(N, p_i)$.*

Theorem 13 (Scaling normal)**.** $X \sim N(\mu, \sigma^2) \implies aX + b \sim N(a\mu + b, a^2\sigma^2)$.

1.1 Sum of Random Variables

Theorem 14 (Convolution)**.**

$$f_{X+Y}(z) = \begin{cases} \sum_{y \in D} f_{X,Y}(z-y, y) = \sum_{x \in D} f_{X,Y}(x, z-x) & \textit{discrete} \\ \int_{-\infty}^{\infty} f_{X,Y}(z-y, y)dy = \int_{-\infty}^{\infty} f_{X,Y}(x, z-x)dx & \textit{continuous} \end{cases}.$$

Theorem 15. *Let* $X_1, \ldots, X_n$ *be independent. Then* $\mathrm{MGF}_t\left(\sum_{i=1}^n X_i\right) = \prod_{i=1}^n \mathrm{MGF}_t(X_i)$.

Theorem 16. *Let* $X_1, \ldots, X_n$ *be independent. Let* $Y := \sum_{i=1}^n X_i$. *Then*

- $X_i \sim \mathrm{Bernouilli}(p) \implies Y \sim \mathrm{Binomial}(n, p)$.
- $X_i \sim \mathrm{Poisson}(\lambda_i) \implies Y \sim \mathrm{Poisson}\left(\sum_{i=1}^n \lambda_i\right)$.
- $X_i \sim \mathrm{Exponential}(\lambda) \implies Y \sim \mathrm{Gamma}(n, \lambda)$.

1.2 Exponential Distribution

Theorem 17. *Let* $X_1, \ldots, X_n$ *be independent ranvars, where* $X_i \sim \mathrm{Expo}(\lambda_i)$. *Let* $Z := \min_{i=1}^n X_i$ *and* E *be the event* $X_1 < X_2 < \ldots < X_n$. *Let* $\beta := \lambda_1 + \ldots + \lambda_n$. *Then*

- $\Pr(X_i = Z) = \lambda_i / \beta$.
- $Z \sim \mathrm{Expo}(\beta)$.
- E *and* Z *are independent.*

2 Inequalities and Limits

Theorem 18 (Markov)**.** *For non-negative randvar* X, $\Pr(X \geq a) \leq \mathrm{E}(X)/a$.

Theorem 19 (Chebyshev)**.** $\Pr(|X - \mathrm{E}(X)| \geq a) \leq \dfrac{\mathrm{Var}(X)}{a^2}$.

Theorem 20 (One-sided Chebyshev)**.**

$$\Pr(X - \mathrm{E}(X) \geq a) \leq \frac{\mathrm{Var}(X)}{\mathrm{Var}(X) + a^2} \qquad \Pr(X - \mathrm{E}(X) \leq -a) \leq \frac{\mathrm{Var}(X)}{\mathrm{Var}(X) + a^2}$$

Theorem 21 (Strong law of large lumbers)**.** *Let* $X_1, X_2, \ldots$ *be IID randvars having mean* μ. *Let* $Y_n := \frac{1}{n} \sum_{i=1}^n X_i$. *Let*

$$E := \left\{ \omega \in \Omega : \lim_{n \to \infty} Y_n(\omega) = \mu \right\}.$$

Then $\Pr(E) = 1$.

Definition 4. *Let* Z *be a random variable and* $S := [X_1, X_2, \ldots]$ *be an infinite sequence of random variables. We say that* S *converges to* Z *if* $\lim_{n \to \infty} F_{X_n}(x) = F_Z(x)$ *for all* $x \in \mathbb{R}$ *where* F_Z *is continuous.*

Theorem 22 (Central Limit Theorem)**.** *Let $X_1, X_2, \ldots$ be IID randvars having mean μ and variance σ^2. Let $Y_n := \sqrt{n}\left(\frac{1}{n}\sum_{i=1}^{n} X_i - \mu\right)$. Then $[Y_1, Y_2, \ldots]$ converges to $N(0, \sigma^2)$.*

Theorem 23 (Jensen's inequality)**.** *If X is a random variable and f is a convex function, then $f(\mathrm{E}(X)) \le \mathrm{E}(f(X))$.*

Theorem 24 (Cauchy-Schwarz inequality)**.** *For random variables X and Y, $|\mathrm{E}(XY)|^2 \le \mathrm{E}(X^2)\,\mathrm{E}(Y^2)$ and $|\mathrm{Cov}(X,Y)|^2 \le \mathrm{Var}(X)\,\mathrm{Var}(Y)$.*

3 Conditional Probability

Theorem 25. *Let X and Y be randvars (either of them can be discrete or continuous). Let f_X and f_Y be their distribution functions (either PMF or PDF), respectively. Let $f_{X,Y}$ be their joint distribution function. Let g_x be the distribution function of Y conditioned on $X = x$. Then $g_x(y) = f_{X,Y}(x,y)/f_X(x)$. We denote $g_x(y)$ by $f_{Y|X}(y \mid x)$.*

Definition 5. *Let X and Y be randvars and A be an event. Let $g(x) := \Pr(A \mid X = x)$ and $h(x) := \mathrm{E}(Y \mid X = x)$. Then $\Pr(A \mid X) := g(X)$ and $\mathrm{E}(Y \mid X) := h(X)$.*

Theorem 26. $\mathrm{E}(\Pr(A \mid X)) = \Pr(A)$ *and* $\mathrm{E}(\mathrm{E}(Y \mid X)) = \mathrm{E}(Y)$.

Theorem 27. $\mathrm{Var}(Y) = \mathrm{E}(\mathrm{Var}(Y \mid X)) + \mathrm{Var}(\mathrm{E}(Y \mid X))$.

4 Binomial Coefficient

The binomial coefficient $\binom{n}{k}$ is the number of subsets of $\{1, 2, \ldots, n\}$ of size k, where $n \in \mathbb{Z}_{\ge 0}$ and $k \in \mathbb{Z}$.

- $\displaystyle\binom{n}{k} = \binom{n}{n-k} = \begin{cases} 0 & \text{if } k < 0 \text{ or } k > n \\ \frac{n!}{k!(n-k)!} & \text{if } 0 \le k \le n \end{cases}.$
- Additive recursion: For $n \ge 1$, $\displaystyle\binom{n}{k} = \binom{n-1}{k} + \binom{n-1}{k-1} = \binom{n+1}{k+1} - \binom{n}{k+1}$.
- Decrement: For $n \ge 1$, $\displaystyle\binom{n}{k} = \frac{n}{k}\binom{n-1}{k-1} = \frac{n}{n-k}\binom{n-1}{k} = \frac{n-k+1}{k}\binom{n}{k-1}$.
- Sum 1: $\displaystyle\sum_{i=k}^{n}\binom{i}{k}\binom{n}{i}x^i = \binom{n}{k}x^k(1+x)^{n-k}$. Set $k = 0$ to get $\displaystyle\sum_{i=0}^{n}\binom{n}{i}x^i = (1+x)^n$.
- Sum 2: $\displaystyle\sum_{i=0}^{p}\binom{m}{i}\binom{n}{p-i} = \binom{m+n}{p}$.
- Sum 3: $\displaystyle\sum_{i=k}^{n-b}\binom{i}{k}\binom{n-i}{b} = \binom{n+1}{k+b+1}$. Set $b = 0$ to get $\displaystyle\sum_{i=k}^{n}\binom{i}{k} = \binom{n+1}{k+1}$.

5 Other useful results

$$\forall x \in \mathbb{R}, \quad e^x \geq 1 + x.$$

$$\forall x > 0, \quad \frac{x-1}{x} \leq \ln x \leq x - 1.$$

$$\forall n \geq 1, \quad \left(\sum_{i=1}^{n} \frac{1}{i}\right) - \ln n \in [1/n, 1].$$

Stirling's approximation: For $n \geq 1$, $\dfrac{n!}{n^{n+\frac{1}{2}} e^{-n}} \in [\sqrt{2\pi}, e]$.

$$\forall a \in \mathbb{Z}, \forall b \in \mathbb{Z}_{>0}, \quad \left\lceil \frac{a}{b} \right\rceil = \left\lfloor \frac{a-1}{b} \right\rfloor + 1 \quad \text{and} \quad \left\lfloor \frac{a}{b} \right\rfloor = \left\lceil \frac{a+1}{b} \right\rceil - 1.$$

Theorem 28 (Generalization of Geometric series)**.** *For $0 \leq a \leq b$,*

$$\sum_{i=0}^{\infty} \binom{b+i}{a} p^i = \frac{1}{1-p} \sum_{i=0}^{a} \binom{b}{i} \left(\frac{p}{1-p}\right)^{a-i}.$$

On setting $b = a$, we get

$$\sum_{i=0}^{\infty} \binom{a+i}{a} p^i = \frac{1}{(1-p)^{a+1}}.$$