

Practice Midterm

Please show your work.

1. X is a random variable with mean 2 and variance $1/4$. Find expectation $E(X/2)$ and standard deviation of $X - 1$.
2. $\{X_1, X_2, \dots, X_{10}\}$ is a sequence of IID follows a Bernoulli distribution with parameter 0.1. That is

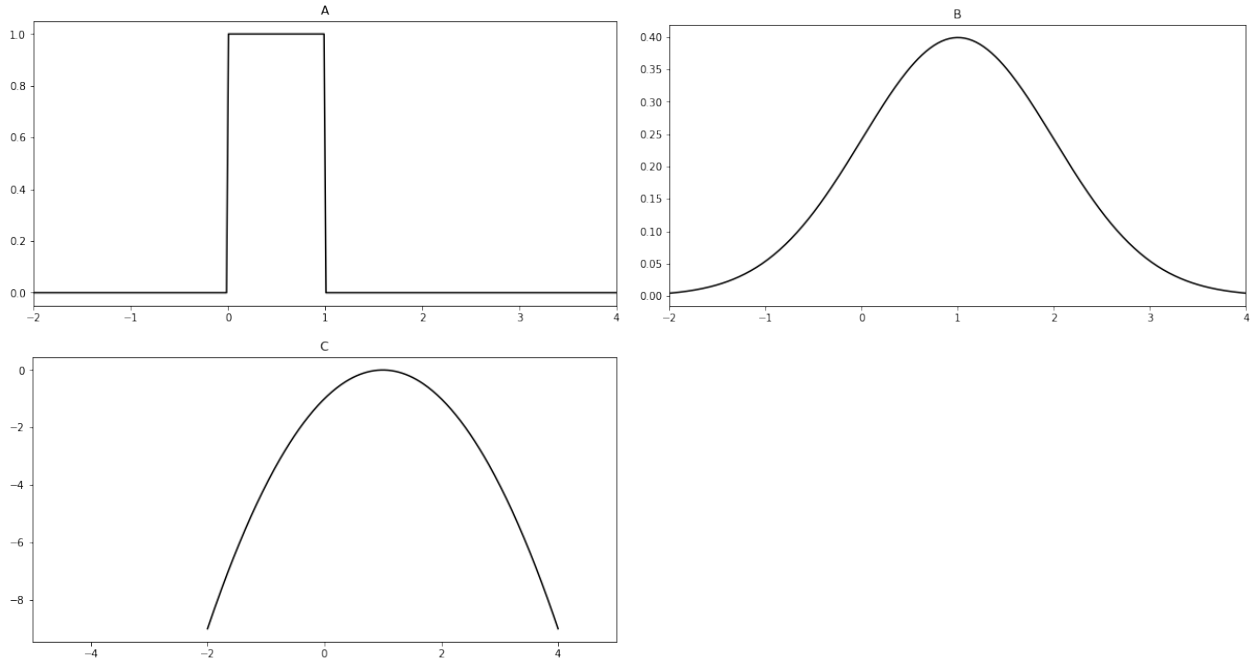
$$p(X_i = 1) = 0.1, p(X_i = 0) = 0.9, E(X_i) = 0.1, Var(X_i) = 0.09$$

. Let $A_{10} = \frac{\sum_{i=1}^{10} X_i}{10}$ Find the following values

- (a) $E(A_{10})$
 - (b) $Var(A_{10})$
 - (c) $std(A_{10})$
 - (d) Use the Central Limit Theorem to find a normal distribution $N(\mu, \sigma^2)$ (i.e. to find μ and σ) to approximate the distribution of A_{10} .
3. Suppose you choose a real number X from the interval $[1, e]$ with a density function of the form:
$$f(x) = \frac{C}{x}$$
where C is a constant. Note that e is the Euler's constant 2.718281....
 - (a) Find C
 - (b) Find $P(E)$, where $E = [1, \frac{e}{2}]$ is a subinterval of $[1, e]$.
 - (c) Find the cumulative density function of X
 4. Let U, V be random numbers chosen independently from the interval $[0, 1]$ uniformly. Find the cumulative distribution and density for the random variable $Y = \max(U, V)$
 5. X follows a Normal Distribution with mean 5 and variance 4. Calculate the following values
 - (a) $P(|X| > 3)$
 - (b) $P(X < 9)$
 - (c) $P(X > 5)$
 - (d) $P(e^X < 1)$

(e) $E(X^2)$

6. X follows a Normal Distribution with mean μ and standard deviation σ . Let Z denote the standard normal distribution. Is it true that $P(|X - \mu| > \sigma)$ is equal to $P(|Z| > 1)$? Justify your answer.
7. Let X be a random variable with $E(X) = 0$ and $Var(X) = 0.01$. What integer value k will assure us that $P(|X| \geq k) \leq 0.01$?
8. Which plot corresponds to a normal distribution?



9. The probability density function of X is $f(x) = \begin{cases} 3(x-1)^2, & \text{if } 2 \geq x \geq 1 \\ 0, & \text{otherwise} \end{cases}$

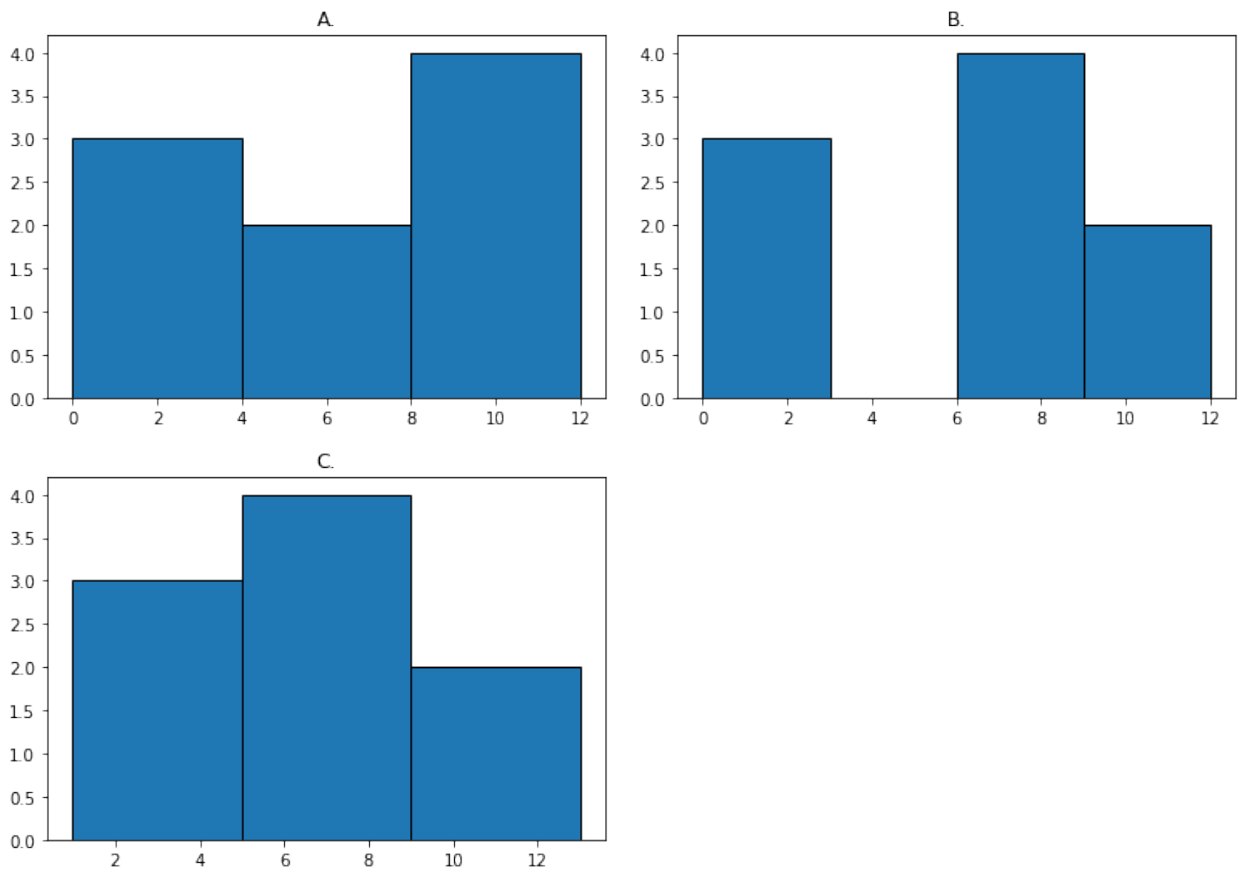
Find the inverse Cumulative Density Function of X

10. Use Hypothesis Testing to answer the question. There are rumors that students at a certain liberal arts college are more inclined to use Gahoo email than U.S. college students in general. Suppose that in a simple random sample of 100 students from the college, 50 admitted to Gahoo email use. Do the data provide enough evidence to conclude that the proportion of Gahoo email users among the students in the college (p) is higher than the national average, which is 0.3?
- (a) Determine Null Hypothesis H_0
- (b) Determine Alternative Hypothesis H_a
- (c) Determine z-score.

- (d) Assume the confidence level is $\alpha = 5\%$. Do the data provide enough evidence to conclude that the proportion of Gahoo email users among the students in the college (p) is higher than the national proportion, which is 0.3?

11. In python, if I run the following code, select the right output graph.

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 data = [1,2,2,7,7.5,8,8.5,9,12]
5 plt.hist(data,bins = 3, range = (0,12),edgecolor='black', linewidth=1)
6 plt.show()
7
```



12. In python, if I run the following code, select the right output.

```
1 arr = np.array([8,9,10,-1])
2 print(np.where(arr<0)[0])
3
```

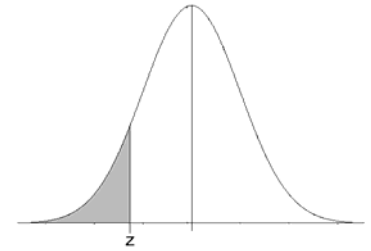
- A. [4]
B. [3]

C. $[-1]$

D. $[10]$

E. None of the above

Standard Normal Cumulative Probability Table



Cumulative probabilities for NEGATIVE z-values are shown in the following table:

z	0.00	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09
-3.4	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0002
-3.3	0.0005	0.0005	0.0005	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0003
-3.2	0.0007	0.0007	0.0006	0.0006	0.0006	0.0006	0.0006	0.0005	0.0005	0.0005
-3.1	0.0010	0.0009	0.0009	0.0009	0.0008	0.0008	0.0008	0.0008	0.0007	0.0007
-3.0	0.0013	0.0013	0.0013	0.0012	0.0012	0.0011	0.0011	0.0011	0.0010	0.0010
-2.9	0.0019	0.0018	0.0018	0.0017	0.0016	0.0016	0.0015	0.0015	0.0014	0.0014
-2.8	0.0026	0.0025	0.0024	0.0023	0.0023	0.0022	0.0021	0.0021	0.0020	0.0019
-2.7	0.0035	0.0034	0.0033	0.0032	0.0031	0.0030	0.0029	0.0028	0.0027	0.0026
-2.6	0.0047	0.0045	0.0044	0.0043	0.0041	0.0040	0.0039	0.0038	0.0037	0.0036
-2.5	0.0062	0.0060	0.0059	0.0057	0.0055	0.0054	0.0052	0.0051	0.0049	0.0048
-2.4	0.0082	0.0080	0.0078	0.0075	0.0073	0.0071	0.0069	0.0068	0.0066	0.0064
-2.3	0.0107	0.0104	0.0102	0.0099	0.0096	0.0094	0.0091	0.0089	0.0087	0.0084
-2.2	0.0139	0.0136	0.0132	0.0129	0.0125	0.0122	0.0119	0.0116	0.0113	0.0110
-2.1	0.0179	0.0174	0.0170	0.0166	0.0162	0.0158	0.0154	0.0150	0.0146	0.0143
-2.0	0.0228	0.0222	0.0217	0.0212	0.0207	0.0202	0.0197	0.0192	0.0188	0.0183
-1.9	0.0287	0.0281	0.0274	0.0268	0.0262	0.0256	0.0250	0.0244	0.0239	0.0233
-1.8	0.0359	0.0351	0.0344	0.0336	0.0329	0.0322	0.0314	0.0307	0.0301	0.0294
-1.7	0.0446	0.0436	0.0427	0.0418	0.0409	0.0401	0.0392	0.0384	0.0375	0.0367
-1.6	0.0548	0.0537	0.0526	0.0516	0.0505	0.0495	0.0485	0.0475	0.0465	0.0455
-1.5	0.0668	0.0655	0.0643	0.0630	0.0618	0.0606	0.0594	0.0582	0.0571	0.0559
-1.4	0.0808	0.0793	0.0778	0.0764	0.0749	0.0735	0.0721	0.0708	0.0694	0.0681
-1.3	0.0968	0.0951	0.0934	0.0918	0.0901	0.0885	0.0869	0.0853	0.0838	0.0823
-1.2	0.1151	0.1131	0.1112	0.1093	0.1075	0.1056	0.1038	0.1020	0.1003	0.0985
-1.1	0.1357	0.1335	0.1314	0.1292	0.1271	0.1251	0.1230	0.1210	0.1190	0.1170
-1.0	0.1587	0.1562	0.1539	0.1515	0.1492	0.1469	0.1446	0.1423	0.1401	0.1379
-0.9	0.1841	0.1814	0.1788	0.1762	0.1736	0.1711	0.1685	0.1660	0.1635	0.1611
-0.8	0.2119	0.2090	0.2061	0.2033	0.2005	0.1977	0.1949	0.1922	0.1894	0.1867
-0.7	0.2420	0.2389	0.2358	0.2327	0.2296	0.2266	0.2236	0.2206	0.2177	0.2148
-0.6	0.2743	0.2709	0.2676	0.2643	0.2611	0.2578	0.2546	0.2514	0.2483	0.2451
-0.5	0.3085	0.3050	0.3015	0.2981	0.2946	0.2912	0.2877	0.2843	0.2810	0.2776
-0.4	0.3446	0.3409	0.3372	0.3336	0.3300	0.3264	0.3228	0.3192	0.3156	0.3121
-0.3	0.3821	0.3783	0.3745	0.3707	0.3669	0.3632	0.3594	0.3557	0.3520	0.3483
-0.2	0.4207	0.4168	0.4129	0.4090	0.4052	0.4013	0.3974	0.3936	0.3897	0.3859
-0.1	0.4602	0.4562	0.4522	0.4483	0.4443	0.4404	0.4364	0.4325	0.4286	0.4247
0.0	0.5000	0.4960	0.4920	0.4880	0.4840	0.4801	0.4761	0.4721	0.4681	0.4641

A normal distribution curve is shown. The area under the curve to the left of a point labeled z on the horizontal axis is shaded gray. The point z is located to the right of the mean (the peak of the curve).

$$Z$$

z	0.00	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09
0.0	0.5000	0.5040	0.5080	0.5120	0.5160	0.5199	0.5239	0.5279	0.5319	0.5359
0.1	0.5398	0.5438	0.5478	0.5517	0.5557	0.5596	0.5636	0.5675	0.5714	0.5753
0.2	0.5793	0.5832	0.5871	0.5910	0.5948	0.5987	0.6026	0.6064	0.6103	0.6141
0.3	0.6179	0.6217	0.6255	0.6293	0.6331	0.6368	0.6406	0.6443	0.6480	0.6517
0.4	0.6554	0.6591	0.6628	0.6664	0.6700	0.6736	0.6772	0.6808	0.6844	0.6879
0.5	0.6915	0.6950	0.6985	0.7019	0.7054	0.7088	0.7123	0.7157	0.7190	0.7224
0.6	0.7257	0.7291	0.7324	0.7357	0.7389	0.7422	0.7454	0.7486	0.7517	0.7549
0.7	0.7580	0.7611	0.7642	0.7673	0.7704	0.7734	0.7764	0.7794	0.7823	0.7852
0.8	0.7881	0.7910	0.7939	0.7967	0.7995	0.8023	0.8051	0.8078	0.8106	0.8133
0.9	0.8159	0.8186	0.8212	0.8238	0.8264	0.8289	0.8315	0.8340	0.8365	0.8389
1.0	0.8413	0.8438	0.8461	0.8485	0.8508	0.8531	0.8554	0.8577	0.8599	0.8621
1.1	0.8643	0.8665	0.8686	0.8708	0.8729	0.8749	0.8770	0.8790	0.8810	0.8830
1.2	0.8849	0.8869	0.8888	0.8907	0.8925	0.8944	0.8962	0.8980	0.8997	0.9015
1.3	0.9032	0.9049	0.9066	0.9082	0.9099	0.9115	0.9131	0.9147	0.9162	0.9177
1.4	0.9192	0.9207	0.9222	0.9236	0.9251	0.9265	0.9279	0.9292	0.9306	0.9319
1.5	0.9332	0.9345	0.9357	0.9370	0.9382	0.9394	0.9406	0.9418	0.9429	0.9441
1.6	0.9452	0.9463	0.9474	0.9484	0.9495	0.9505	0.9515	0.9525	0.9535	0.9545
1.7	0.9554	0.9564	0.9573	0.9582	0.9591	0.9599	0.9608	0.9616	0.9625	0.9633
1.8	0.9641	0.9649	0.9656	0.9664	0.9671	0.9678	0.9686	0.9693	0.9699	0.9706
1.9	0.9713	0.9719	0.9726	0.9732	0.9738	0.9744	0.9750	0.9756	0.9761	0.9767
2.0	0.9772	0.9778	0.9783	0.9788	0.9793	0.9798	0.9803	0.9808	0.9812	0.9817
2.1	0.9821	0.9826	0.9830	0.9834	0.9838	0.9842	0.9846	0.9850	0.9854	0.9857
2.2	0.9861	0.9864	0.9868	0.9871	0.9875	0.9878	0.9881	0.9884	0.9887	0.9890
2.3	0.9893	0.9896	0.9898	0.9901	0.9904	0.9906	0.9909	0.9911	0.9913	0.9916
2.4	0.9918	0.9920	0.9922	0.9925	0.9927	0.9929	0.9931	0.9932	0.9934	0.9936
2.5	0.9938	0.9940	0.9941	0.9943	0.9945	0.9946	0.9948	0.9949	0.9951	0.9952
2.6	0.9953	0.9955	0.9956	0.9957	0.9959	0.9960	0.9961	0.9962	0.9963	0.9964
2.7	0.9965	0.9966	0.9967	0.9968	0.9969	0.9970	0.9971	0.9972	0.9973	0.9974
2.8	0.9974	0.9975	0.9976	0.9977	0.9977	0.9978	0.9979	0.9979	0.9980	0.9981
2.9	0.9981	0.9982	0.9982	0.9983	0.9984	0.9984	0.9985	0.9985	0.9986	0.9986
3.0	0.9987	0.9987	0.9987	0.9988	0.9988	0.9989	0.9989	0.9989	0.9990	0.9990
3.1	0.9990	0.9991	0.9991	0.9991	0.9992	0.9992	0.9992	0.9992	0.9993	0.9993
3.2	0.9993	0.9993	0.9994	0.9994	0.9994	0.9994	0.9994	0.9995	0.9995	0.9995
3.3	0.9995	0.9995	0.9995	0.9996	0.9996	0.9996	0.9996	0.9996	0.9996	0.9997
3.4	0.9997	0.9997	0.9997	0.9997	0.9997	0.9997	0.9997	0.9997	0.9997	0.9998

Probability Cheat Sheet

Distributions

Unifrom Distribution

notation	$U[a, b]$
cdf	$\frac{x-a}{b-a}$ for $x \in [a, b]$
pdf	$\frac{1}{b-a}$ for $x \in [a, b]$
expectation	$\frac{1}{2}(a+b)$
variance	$\frac{1}{12}(b-a)^2$
mgf	$\frac{e^{tb} - e^{ta}}{t(b-a)}$

story: all intervals of the same length on the distribution's support are equally probable.

Gamma Distribution

notation	$Gamma(k, \theta)$
pdf	$\frac{\theta^k x^{k-1} e^{-\theta x}}{\Gamma(k)} \mathbb{I}_{x>0}$ $\Gamma(k) = \int_0^\infty x^{k-1} e^{-x} dx$
expectation	$k\theta$
variance	$k\theta^2$
mgf	$(1 - \theta t)^{-k}$ for $t < \frac{1}{\theta}$
ind. sum	$\sum_{i=1}^n X_i \sim Gamma\left(\sum_{i=1}^n k_i, \theta\right)$

story: the sum of k independent exponentially distributed random variables, each of which has a mean of θ (which is equivalent to a rate parameter of θ^{-1}).

Geometric Distribution

notation	$G(p)$
cdf	$1 - (1-p)^k$ for $k \in \mathbb{N}$
pmf	$(1-p)^{k-1} p$ for $k \in \mathbb{N}$
expectation	$\frac{1}{p}$
variance	$\frac{1-p}{p^2}$
mgf	$\frac{pe^t}{1 - (1-p)e^t}$

story: the number X of Bernoulli trials needed to get one success. Memoryless.

Poisson Distribution

notation	$Poisson(\lambda)$
cdf	$e^{-\lambda} \sum_{i=0}^k \frac{\lambda^i}{i!}$
pmf	$\frac{\lambda^k}{k!} \cdot e^{-\lambda}$ for $k \in \mathbb{N}$
expectation	λ
variance	λ
mgf	$\exp(\lambda(e^t - 1))$
ind. sum	$\sum_{i=1}^n X_i \sim Poisson\left(\sum_{i=1}^n \lambda_i\right)$

story: the probability of a number of events occurring in a fixed period of time if these events occur with a known average rate and independently of the time since the last event.

Normal Distribution

notation	$N(\mu, \sigma^2)$
pdf	$\frac{1}{\sqrt{2\pi}\sigma^2} e^{-(x-\mu)^2/(2\sigma^2)}$
expectation	μ
variance	σ^2
mgf	$\exp\left(\mu t + \frac{1}{2}\sigma^2 t^2\right)$
ind. sum	$\sum_{i=1}^n X_i \sim N\left(\sum_{i=1}^n \mu_i, \sum_{i=1}^n \sigma_i^2\right)$

story: describes data that cluster around the mean.

Standard Normal Distribution

notation	$N(0, 1)$
cdf	$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-t^2/2} dt$
pdf	$\frac{1}{\sqrt{2\pi}} e^{-x^2/2}$
expectation	$\frac{1}{\lambda}$
variance	$\frac{1}{\lambda^2}$
mgf	$\exp\left(\frac{t^2}{2}\right)$

story: normal distribution with $\mu = 0$ and $\sigma = 1$.

Exponential Distribution

notation	$exp(\lambda)$
cdf	$1 - e^{-\lambda x}$ for $x \geq 0$
pdf	$\lambda e^{-\lambda x}$ for $x \geq 0$
expectation	$\frac{1}{\lambda}$
variance	$\frac{1}{\lambda^2}$
mgf	$\frac{\lambda - t}{\lambda^2}$
ind. sum	$\sum_{i=1}^k X_i \sim Gamma(k, \lambda)$
minimum	$\sim exp\left(\sum_{i=1}^k \lambda_i\right)$

story: the amount of time until some specific event occurs, starting from now, being memoryless.

Binomial Distribution

notation	$Bin(n, p)$
cdf	$\sum_{i=0}^k \binom{n}{i} p^i (1-p)^{n-i}$
pmf	$\binom{n}{i} p^i (1-p)^{n-i}$
expectation	np
variance	$np(1-p)$
mgf	$(1-p + pe^t)^n$

story: the discrete probability distribution of the number of successes in a sequence of n independent yes/no experiments, each of which yields success with probability p .

Basics

Cumulative Distribution Function

$$F_X(x) = \mathbb{P}(X \leq x)$$

Probability Density Function

$$F_X(x) = \int_{-\infty}^{\infty} f_X(t) dt$$

$$\int_{-\infty}^{\infty} f_X(t) dt = 1$$

$$f_X(x) = \frac{d}{dx} F_X(x)$$

Quantile Function

The function $X^* : [0, 1] \rightarrow \mathbb{R}$ for which for any $p \in [0, 1]$, $F_X(X^*(p)^-) \leq p \leq F_X(X^*(p))$

$$F_{X^*} = F_X$$

$$\mathbb{E}(X^*) = \mathbb{E}(X)$$

Expectation

$$\mathbb{E}(X) = \int_0^1 X^*(p) dp$$

$$\mathbb{E}(X) = \int_{-\infty}^0 F_X(t) dt + \int_0^\infty (1 - F_X(t)) dt$$

$$\mathbb{E}(X) = \int_{-\infty}^{\infty} x f_X(x) dx$$

$$\mathbb{E}(g(X)) = \int_{-\infty}^{\infty} g(x) f_X(x) dx$$

$$\mathbb{E}(aX + b) = a\mathbb{E}(X) + b$$

Variance

$$\text{Var}(X) = \mathbb{E}(X^2) - (\mathbb{E}(X))^2$$

$$\text{Var}(X) = \mathbb{E}((X - \mathbb{E}(X))^2)$$

$$\text{Var}(aX + b) = a^2 \text{Var}(X)$$

Standard Deviation

$$\sigma(X) = \sqrt{\text{Var}(X)}$$

Covariance

$$\text{Cov}(X, Y) = \mathbb{E}(XY) - \mathbb{E}(X)\mathbb{E}(Y)$$

$$\text{Cov}(X, Y) = \mathbb{E}((X - \mathbb{E}(X))(Y - \mathbb{E}(Y)))$$

$$\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X, Y)$$

Correlation Coefficient

$$\rho_{X,Y} = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}$$

Moment Generating Function

$$M_X(t) = \mathbb{E}(e^{tX})$$

$$\mathbb{E}(X^n) = M_X^{(n)}(0)$$

$$M_{aX+b}(t) = e^{tb} M_{aX}(t)$$

Joint Distribution

$$\mathbb{P}_{X,Y}(B) = \mathbb{P}((X,Y) \in B)$$
$$F_{X,Y}(x,y) = \mathbb{P}(X \leq x, Y \leq y)$$

Joint Density

$$\mathbb{P}_{X,Y}(B) = \iint_B f_{X,Y}(s,t) dsdt$$
$$F_{X,Y}(x,y) = \int_{-\infty}^x \int_{-\infty}^y f_{X,Y}(s,t) dt ds$$
$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(s,t) dsdt = 1$$

Marginal Distributions

$$\mathbb{P}_X(B) = \mathbb{P}_{X,Y}(B \times \mathbb{R})$$
$$\mathbb{P}_Y(B) = \mathbb{P}_{X,Y}(\mathbb{R} \times Y)$$
$$F_X(a) = \int_{-\infty}^a \int_{-\infty}^{\infty} f_{X,Y}(s,t) dt ds$$
$$F_Y(b) = \int_{-\infty}^b \int_{-\infty}^{\infty} f_{X,Y}(s,t) ds dt$$

Marginal Densities

$$f_X(s) = \int_{-\infty}^{\infty} f_{X,Y}(s,t) dt$$
$$f_Y(t) = \int_{-\infty}^{\infty} f_{X,Y}(s,t) ds$$

Joint Expectation

$$\mathbb{E}(\varphi(X,Y)) = \iint_{\mathbb{R}^2} \varphi(x,y) f_{X,Y}(x,y) dx dy$$

Independent r.v.

$$\mathbb{P}(X \leq x, Y \leq y) = \mathbb{P}(X \leq x) \mathbb{P}(Y \leq y)$$
$$F_{X,Y}(x,y) = F_X(x) F_Y(y)$$
$$f_{X,Y}(s,t) = f_X(s) f_Y(t)$$
$$\mathbb{E}(XY) = \mathbb{E}(X) \mathbb{E}(Y)$$
$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y)$$

Independent events:

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

Conditional Probability

$$\mathbb{P}(A | B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}$$
$$\text{bayes } \mathbb{P}(A | B) = \frac{\mathbb{P}(B | A) \mathbb{P}(A)}{\mathbb{P}(B)}$$

Conditional Density

$$f_{X|Y=y}(x) = \frac{f_{X,Y}(x,y)}{f_Y(y)}$$
$$f_{X|Y=n}(x) = \frac{f_X(x) \mathbb{P}(Y=n | X=x)}{\mathbb{P}(Y=n)}$$
$$F_{X|Y=y} = \int_{-\infty}^x f_{X|Y=y}(t) dt$$

Conditional Expectation

$$\mathbb{E}(X | Y=y) = \int_{-\infty}^{\infty} x f_{X|Y=y}(x) dx$$
$$\mathbb{E}(\mathbb{E}(X | Y)) = \mathbb{E}(X)$$
$$\mathbb{P}(Y=n) = \mathbb{E}(\mathbb{I}_{Y=n}) = \mathbb{E}(\mathbb{E}(\mathbb{I}_{Y=n} | X))$$

Sequences and Limits

$$\limsup A_n = \{A_n \text{ i.o.}\} = \bigcap_{m=1}^{\infty} \bigcup_{n=m}^{\infty} A_n$$
$$\liminf A_n = \{A_n \text{ eventually}\} = \bigcup_{m=1}^{\infty} \bigcap_{n=m}^{\infty} A_n$$

$$\liminf A_n \subseteq \limsup A_n$$
$$(\limsup A_n)^c = \liminf A_n^c$$
$$(\liminf A_n)^c = \limsup A_n^c$$

$$\mathbb{P}(\limsup A_n) = \lim_{n \rightarrow \infty} \mathbb{P}\left(\bigcup_{n=m}^{\infty} A_n\right)$$
$$\mathbb{P}(\liminf A_n) = \lim_{n \rightarrow \infty} \mathbb{P}\left(\bigcap_{n=m}^{\infty} A_n\right)$$

Borel-Cantelli Lemma

$$\sum_{n=1}^{\infty} \mathbb{P}(A_n) < \infty \Rightarrow \mathbb{P}(\limsup A_n) = 0$$

And if A_n are independent:

$$\sum_{n=1}^{\infty} \mathbb{P}(A_n) = \infty \Rightarrow \mathbb{P}(\limsup A_n) = 1$$

Convergence

Convergence in Probability

notation $X_n \xrightarrow{p} X$

meaning $\lim_{n \rightarrow \infty} \mathbb{P}(|X_n - X| > \varepsilon) = 0$

Convergence in Distribution

notation $X_n \xrightarrow{D} X$

meaning $\lim_{n \rightarrow \infty} F_n(x) = F(x)$

Almost Sure Convergence

notation $X_n \xrightarrow{a.s.} X$

meaning $\mathbb{P}\left(\lim_{n \rightarrow \infty} X_n = X\right) = 1$

Criteria for a.s. Convergence

- $\forall \varepsilon \exists N \forall n > N : \mathbb{P}(|X_n - X| < \varepsilon) > 1 - \varepsilon$
- $\forall \varepsilon \mathbb{P}(\limsup (|X_n - X| > \varepsilon)) = 0$
- $\forall \varepsilon \sum_{n=1}^{\infty} \mathbb{P}(|X_n - X| > \varepsilon) < \infty$ (by B.C.)

Convergence in L_p

notation $X_n \xrightarrow{L_p} X$

meaning $\lim_{n \rightarrow \infty} \mathbb{E}(|X_n - X|^p) = 0$

Relationships

$$\begin{array}{ccc} \xrightarrow{L_q} & \Rightarrow_{q>p \geq 1} & \xrightarrow{L_p} \\ & \Downarrow & \\ \xrightarrow{a.s.} & \Rightarrow & \xrightarrow{p} \Rightarrow \xrightarrow{D} \end{array}$$

If $X_n \xrightarrow{D} c$ then $X_n \xrightarrow{p} c$
If $X_n \xrightarrow{p} X$ then there exists a subsequence n_k s.t. $X_{n_k} \xrightarrow{a.s.} X$

Laws of Large Numbers

If X_i are i.i.d. r.v.,

weak law $\overline{X_n} \xrightarrow{p} \mathbb{E}(X_1)$

strong law $\overline{X_n} \xrightarrow{a.s.} \mathbb{E}(X_1)$

Central Limit Theorem

$$\frac{S_n - n\mu}{\sigma\sqrt{n}} \xrightarrow{D} N(0,1)$$

If $t_n \rightarrow t$, then

$$\mathbb{P}\left(\frac{S_n - n\mu}{\sigma\sqrt{n}} \leq t_n\right) \rightarrow \Phi(t)$$

Inequalities

Markov's inequality

$$\mathbb{P}(|X| \geq t) \leq \frac{\mathbb{E}(|X|)}{t}$$

Chebyshev's inequality

$$\mathbb{P}(|X - \mathbb{E}(X)| \geq \varepsilon) \leq \frac{\text{Var}(X)}{\varepsilon^2}$$

Chernoff's inequality

Let $X \sim \text{Bin}(n, p)$; then:

$$\mathbb{P}(X - \mathbb{E}(X) > t\sigma(X)) < e^{-t^2/2}$$

Simpler result; for every X :

$$\mathbb{P}(X \geq a) \leq M_X(t) e^{-ta}$$

Jensen's inequality

for φ a convex function, $\varphi(\mathbb{E}(X)) \leq \mathbb{E}(\varphi(X))$

Miscellaneous

$$\mathbb{E}(Y) < \infty \iff \sum_{n=0}^{\infty} \mathbb{P}(Y > n) < \infty \quad (Y \geq 0)$$

$$\mathbb{E}(X) = \sum_{n=0}^{\infty} \mathbb{P}(X > n) \quad (X \in \mathbb{N})$$

$$X \sim U(0,1) \iff -\ln X \sim \exp(1)$$

Convolution

For ind. $X, Y, Z = X + Y$:

$$f_Z(z) = \int_{-\infty}^{\infty} f_X(s) f_Y(z-s) ds$$

Kolmogorov's 0-1 Law

If A is in the tail σ -algebra \mathcal{F}^t , then $\mathbb{P}(A) = 0$ or $\mathbb{P}(A) = 1$

Ugly Stuff

cdf of Gamma distribution:

$$\int_0^t \frac{\theta^k x^{k-1} e^{-\theta x}}{(k-1)!} dx$$

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