4.3 Transforms

Transforms often provide us convenient ways with regard to certain mathematical manipulations.

The transform, in other words, the moment generating function (MGF), of a r.v. \( X \) is defined as

\[
M_X(s) = E[e^{sx}].
\]

Discrete case MGF: \( M_X(s) = \sum_x e^{sx}p_X(x) \)
Continuous case MGF: \( M_X(s) = \int_{-\infty}^{\infty} e^{sx}f_X(x)dx \)

**Ex:** MGF of a Poisson r.v.

**Ex:** MGF of an exponential r.v.

**Ex:** MGF of a linear function of a r.v.
Ex: MGF of a Gaussian random variable with mean $\mu$ and variance $\sigma^2$.

Ex: Using the MGF of the Gaussian, and the property we just proved about the transform of a linear function of a random variable, show that a linear function of a Gaussian r.v. is also Gaussian.

4.3.1 Computation of Moments from Transforms

The name moment generating function follows from the following property.

$$E[X^n] = \frac{d^n}{ds^n} M_X(s) |_{s=0}$$

Proof:
Ex: Mean and variance of an exponential r.v.

Note: The transform $M_X(s)$ of a r.v. $X$ uniquely determines the PDF of $X$. That is, one can always find $f_X(x)$ from $M_X(s)$.

4.3.2 Mixture of two distributions

Ex: The length in KBytes of IP packets received at a switch are, with 80% probability, exponentially distributed with mean 10, and with 20% probability, exponentially distributed with mean 100. Determine the MGF of the length of a randomly (uniformly) selected packet.
4.3.3 Sums of Independent R.V.s

When \( X_1, X_2, \ldots, X_k \) are independent r.v.s, the MGF of their sum \( Y = \sum_{i=1}^{k} X_i \) has a simple form. In deriving it, one may interpret \( e^{sX_i} \) as a function of \( X_i \).

**Ex:** Sum of independent Poisson r.v.s

**Ex:** The sum of two independent Gaussian random variables is Gaussian. Let \( X \sim \mathcal{N}(\mu_1, \sigma_1^2) \), and \( Y \sim \mathcal{N}(\mu_2, \sigma_2^2) \).