

# 8.08 Statistical Physics II — Spring 2019

## Recitation Note 12

Huitao Shen  
huitao@mit.edu

May 13, 2019

### Contents

<b>1</b>	<b>Lattice Random Walk</b>	<b>2</b>
1.1	One Dimension . . . . .	2
1.2	Higher Dimensions . . . . .	3
<b>2</b>	<b>Continuous Random Walk and Diffusion</b>	<b>4</b>
2.1	Fokker-Planck Equation . . . . .	4
2.2	Einstein Relation . . . . .	4

# 1 Lattice Random Walk

## 1.1 One Dimension

Consider the random walk on an one-dimensional lattice. At each time step, the particle jumps to the right with probability  $q$  and left with probability  $1 - q$ . The distance of each jump is  $l$ . In the context of kinetics,  $l$  is the mean free path.

Denote  $x_n$  as the movement at  $n$ -th step. By definition,  $x_n$  is a Bernoulli random variable  $x_n \sim \text{Ber}(p)$ . Different  $x_n$ ,  $n \in \mathbb{N}$  are independent. The position of the particle after  $N$  steps is  $x_N = \sum_{i=1}^N x_i$ . By the linearity of the expectation:

$$\mu_N \equiv \langle x_N \rangle = \sum_{i=1}^N \langle x_i \rangle = N \langle x_1 \rangle = N [ql - (1 - q)l] = Nl(2q - 1). \quad (1)$$

For a symmetric random walk  $q = 1/2$ ,  $\mu_N = 0$  due to the symmetry.

To compute the variance of  $x_N$ ,

$$\langle x_N^2 \rangle = \left\langle \left( \sum_{i=1}^N x_i \right) \left( \sum_{j=1}^N x_j \right) \right\rangle = \sum_{i,j=1}^N \langle x_i x_j \rangle \quad (2)$$

$$= \sum_{i=1}^N \langle x_i^2 \rangle + 2 \sum_{1 \leq i < j \leq N} \langle x_i \rangle \langle x_j \rangle \quad (3)$$

$$= Nl^2 + N(N - 1)l^2(2q - 1)^2. \quad (4)$$

It follows

$$\sigma_N^2 \equiv \langle x_N^2 \rangle - \langle x_N \rangle^2 = 4Nl^2q(1 - q), \quad (5)$$

which is maximized when  $q = 1/2$  and is zero when  $q = 0$  or  $1$ . Note that  $\sigma_N^2 \sim N$  instead of  $N^2$ .

One can also compute the probability mass function of  $x_N$ . The probability that the particle jumps right  $k$  times among the first  $N$  steps is

$$p(k, N) = \binom{N}{k} p^k (1 - p)^{N-k}, \quad (6)$$

and  $x$  is related to  $k$  as

$$x = kl - (N - k)l = (2k - N)l. \quad (7)$$

Essentially, this is the probability mass function of a binomial random variable, which is the independent sum of identical Bernoulli random variables.

Perhaps it is more illuminating to consider the  $N \rightarrow \infty$  limit. According to the central limit theorem,  $x_N$  tends to distributed normally  $x_N \sim \mathcal{N}(\mu_N, \sigma_N^2)$ :

$$p(x, N) = \frac{1}{\sqrt{2\pi}\sigma_N} e^{-\frac{(x - \mu_N)^2}{2\sigma_N^2}}. \quad (8)$$

This is a Gaussian wave packet, whose center drifts with velocity  $\mu_N/N = l(2q - 1)$ , and whose size spreads out with time.

We now restrict ourselves to the symmetric/unbiased random walk  $q = 1/2$ . The probability that the particle returns to the origin after  $2n$  steps is:

$$P(x_{2n} = 0) = \frac{1}{2^{2n}} \binom{2n}{n} \sim \frac{1}{\sqrt{\pi n}}, \quad (9)$$

where we have used Stirling's approximation:

$$n! \sim \sqrt{2\pi n} \left(\frac{n}{e}\right)^n. \quad (10)$$

Define the indicator random variable  $X_n = 1$  if  $x_n = 0$ .  $X = \sum_{i=1}^{\infty} X_i$  counts the total number of returns. Then

$$\langle X \rangle = \sum_{i=1}^{\infty} \langle X_i \rangle = \sum_{i=1}^{\infty} P(x_{2i} = 0) \sim \frac{1}{\sqrt{\pi}} \sum_{i=1}^{\infty} \frac{1}{\sqrt{i}} = \infty, \quad (11)$$

which diverges.

The expected number of returns  $\langle X \rangle$  is related to the probability of return. Denote  $\rho$  as the probability that the particle ever returns to the origin, and  $\rho_k$  as the probability that the particle returns to the origin exactly  $k$  times. Obviously

$$\rho_k = \rho^k (1 - \rho), \quad (12)$$

by treating the whole random walk as  $k + 1$  independent random walks. In this way,

$$\langle X \rangle = \sum_{i=1}^{\infty} i \rho_i = (1 - \rho) \sum_{i=1}^{\infty} i \rho^i = \frac{\rho}{1 - \rho}. \quad (13)$$

Therefore,

$$\begin{aligned} \langle X \rangle = \infty &\Leftrightarrow \rho = 1, \\ \langle X \rangle < \infty &\Leftrightarrow \rho < 1. \end{aligned}$$

The return probability of one-dimensional symmetric random walk is one  $\rho_{1D} = 1$ .

## 1.2 Higher Dimensions

Random walks in higher dimensions can be treated similarly to the one-dimensional case. In the following, will only focus on the return probability  $\rho$  for symmetric random walks.

In two dimensions, the probability the particle returns to the origin after  $2n$  steps is

$$P(\mathbf{x}_{2n} = 0) = \frac{1}{4^{2n}} \sum_{k=0}^n \binom{2n}{k} \binom{2n-k}{k} \binom{2n-2k}{n-k} \quad (14)$$

$$= \frac{1}{4^{2n}} \sum_{k=0}^n \frac{(2n)!}{(k!)^2 ((n-k)!)^2} \quad (15)$$

$$= \frac{1}{4^{2n}} \sum_{k=0}^n \binom{2n}{n} \binom{n}{k}^2 \quad (16)$$

$$= \frac{1}{4^{2n}} \binom{2n}{n} \sum_{k=0}^n \binom{n}{k} \binom{n}{n-k} \quad (17)$$

$$= \frac{1}{4^{2n}} \binom{2n}{n}^2, \quad (18)$$

where the particle goes up and down  $k$  times and left and right  $n - k$  times. In the last line, we use the fact that choosing  $n$  from  $2n$  items can be achieved by dividing  $2n$  items into two piles of  $n$  items, then pick  $k$  items from the first pile and  $n - k$  from the second.

Notice  $P(\mathbf{x}_{2n} = 0)$  is exactly the square of its one-dimensional counterpart. Now, the expected number of returns is

$$\langle X \rangle = \sum_{i=1}^{\infty} P(\mathbf{x}_{2i} = 0) \sim \frac{1}{\pi} \sum_{i=1}^{\infty} \frac{1}{i} = \infty. \quad (19)$$

Therefore, the return probability of two-dimensional symmetric random walk is also  $\rho_{2D} = 1$ .

In three dimensions, the computation is more complicated. At the end of the day,  $\langle X \rangle$  is related to  $C \sum_{i=1}^{\infty} 1/i^{3/2} < \infty$ . Therefore,  $\rho_{3D} < 1$ . This result was first proved by Pólya in 1921. In fact,  $\rho_{3D} \approx 0.34$ , and the probability decreases with increasing the dimensions<sup>1</sup>. Random walks with  $\rho = 1$  are called “recurrent”, and those with  $\rho < 1$  are called “transient”. There is a famous quote by Shizuo Kakutani:

A drunk man will find his way home, but a drunk bird may get lost forever.

## 2 Continuous Random Walk and Diffusion

### 2.1 Fokker-Planck Equation

$p(x, N)$  can be derived recursively instead of directly. It is not hard to see

$$p(x, N + 1) = qp(x - l, N) + (1 - q)p(x + l, N). \quad (20)$$

This is the master equation. The initial condition is  $p(x, 0) = \delta(x)$ . In the limit of small jumps and small time steps, the master equation reduces to

$$p(x, t + \Delta t) = qp(x - \Delta x, t) + (1 - q)p(x + \Delta x, t). \quad (21)$$

By Taylor expanding  $p(x, t)$  to second order:

$$\frac{\partial p}{\partial t} = -v \frac{\partial p}{\partial x} + D \frac{\partial^2 p}{\partial x^2}, \quad (22)$$

where

$$v \equiv (2q - 1) \frac{\Delta x}{\Delta t}, \quad D \equiv \frac{\Delta x^2}{2\Delta t}, \quad (23)$$

are the drift velocity and the diffusion constant respectively. This is Fokker-Planck equation. In general, both  $v$  and  $D$  can be position-dependent, and the Fokker-Planck equation becomes

$$\frac{\partial p(x, t)}{\partial t} = -\frac{\partial}{\partial x} v(x)p(x, t) + \frac{\partial^2}{\partial x^2} D(x)p(x, t). \quad (24)$$

Since probability is conserved, Fokker-Planck equation can be rewritten into the continuity equation

$$\frac{\partial p(x, t)}{\partial t} = -\frac{\partial J(x, t)}{\partial x}, \quad (25)$$

where the probability current

$$J(x, t) \equiv v(x)p(x, t) - \frac{\partial}{\partial x} D(x)p(x, t). \quad (26)$$

Fokker-Planck equation is equivalent to Fick’s law of diffusion. In this way, we have derived the Fick’s law from the microscopic random walk model. The phenomenological parameter  $v$  and  $D$  relates to the microscopic parameter according to Eq. (24).

### 2.2 Einstein Relation

At equilibrium, there is no probability flow  $J(x, t) = 0$  and the probability distribution is given by

$$p(x) \propto \frac{1}{D(x)} \exp\left(\int_{-\infty}^x dy \frac{v(y)}{D(y)}\right). \quad (27)$$

<sup>1</sup>See <http://mathworld.wolfram.com/PolyasRandomWalkConstants.html>.

Consider a particle moving in a fluid. According to Newton's second law:

$$m \frac{d^2x}{dt^2} = -\lambda v(x) - \frac{\partial U(x)}{\partial x} + F_r, \quad (28)$$

where  $\lambda$  is the drag coefficient and  $F_r$  is the random Brownian force. At equilibrium,  $d^2x/dt^2 = 0$  and

$$\langle v(x) \rangle = -\frac{1}{\lambda} \frac{\partial U(x)}{\partial x}. \quad (29)$$

Insert into Eq. (27) and let  $D$  be a constant,

$$p(x) \propto \exp\left(-\frac{U(x)}{\lambda D}\right). \quad (30)$$

On the other hand, according to Boltzmann distribution:

$$p(x) \propto \exp\left(-\frac{U(x)}{k_B T}\right). \quad (31)$$

Therefore,

$$D = \frac{k_B T}{\lambda}. \quad (32)$$

This is the Einstein relation, which was proposed by Einstein in 1905. Essentially, the relation states that the same random forces that cause the erratic motion of a particle in Brownian motion would also cause drag if the particle were pulled through the fluid. It is an example of the fluctuation–dissipation relation.