

**Physics 112 - Intro to Statistical and Thermal Physics - Spring 2023**  
**Spoiler Set 04**

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**Problem 4.2 - Diffusion**

(a) Instead of the setup where we have temperature  $T$  on the left of the boundary and slightly higher temperature  $T + dT$  on the right, use a setup where the temperatures are equal but we have a concentration  $n$  on the left and slightly higher concentration  $n + dn$  on the right.

(e) You should find to within an order of magnitude that  $D \sim 10^{-5} \text{m}^2/\text{s}$ .

(f) This is an order-of-magnitude estimation problem involving a differential equation. A good way to approach this is to replace the partials with scales for the quantities. That is, we can replace something like  $\frac{\partial^2 n}{\partial x^2}$  with  $N/x^2$ , where  $N$  is a typical number scale for the number of particles involved (sub-spoiler: this will wind up canceling out!) and  $x$  is the typical length scale for distances involved. Our goal is to find a time-scale.

Some chemistry! The “fruity” smell of perfume is from the compound ethyl octanoate,  $\text{C}_{10}\text{H}_{20}\text{O}_2$ . You can use this to estimate the relative mass and size of the perfume molecules as compared to air.

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**Problem 4.3 - Biased Random Walks and Binary State Systems**

(a) **Extra Part** (*Not for Credit*) In the  $N = 4$  case there are 16 microstates with macrostates and multiplicities  $X = \pm 4\ell$  with  $\Omega = 1$ ;  $X = \pm 2\ell$  with  $\Omega = 4$ ;  $X = 0$  with  $\Omega = 6$ .

(d) Remember that the expectation value/average of some function  $f(X)$  of our variable  $X$  is given by  $\langle f(X) \rangle = \sum_i f(X_i)P(X_i)$ .

(e) Since the  $\Delta x_i$  are all independent,  $\langle \Delta x_i \rangle$  will be the same for all values of  $i$ .

(f) You can express  $\langle \Delta x_i \Delta x_j \rangle$  using the Kronecker delta as  $\delta_{ij}(\text{answer when } i = j) + (1 - \delta_{ij})(\text{answer when } i \neq j)$ .

You should find  $\langle \Delta x_i \Delta x_j \rangle = \ell^2 (\delta_{ij} + (1 - \delta_{ij})(p_R - p_L)^2)$ .

(h) The  $X$  that maximizes  $P(X)$  will also be the  $X$  that maximizes  $\ln P(X)$ . The logarithm will be easier to work with!

You should find that the maximum occurs when  $n = pN$ .

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## Problem 4.4 - DataHub - Biased Random Walks

For part (a), you can generate the random walk by first generating an array of  $N$  random numbers chosen uniformly between 0 and 1. Numpy has a function that does this nicely. Once you have the array of numbers, you can convert that to a microstate by, for example, saying if a given number is less than  $\theta$  then we will call that “spin up” and otherwise call it “spin down.” Think about why that works!

