

# Introduction to Neural Computation – 9.40

- Prof. Michale Fee, Instructor
- Daniel Zysman, Technical instructor

# Texts: *Selected readings*

- Berg, Random Walks in Biology
- Dayan & Abbott, Theoretical Neuroscience.
- Hille, Ionic Channels of Excitable Membranes  
...and others

# What is neural computation?

- Brain and cognitive sciences are no longer primarily descriptive
  - Engineering-level descriptions of brain systems.

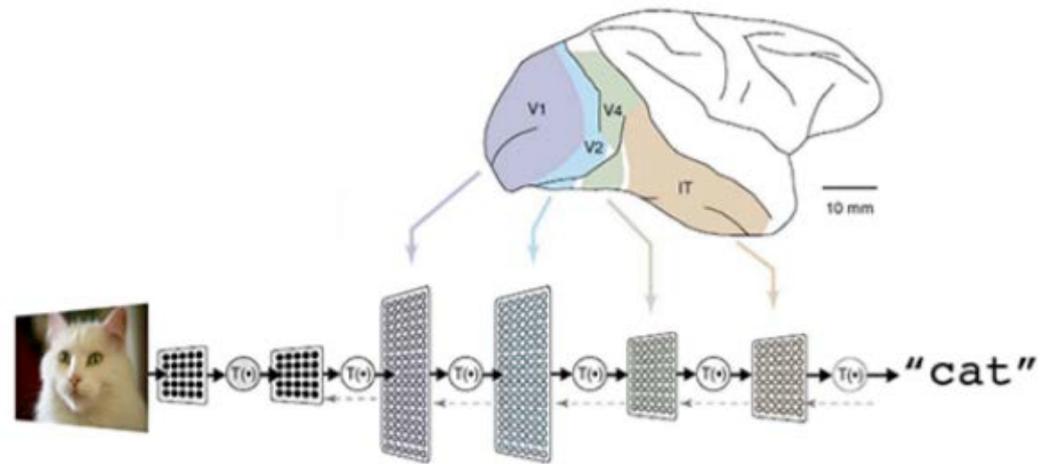
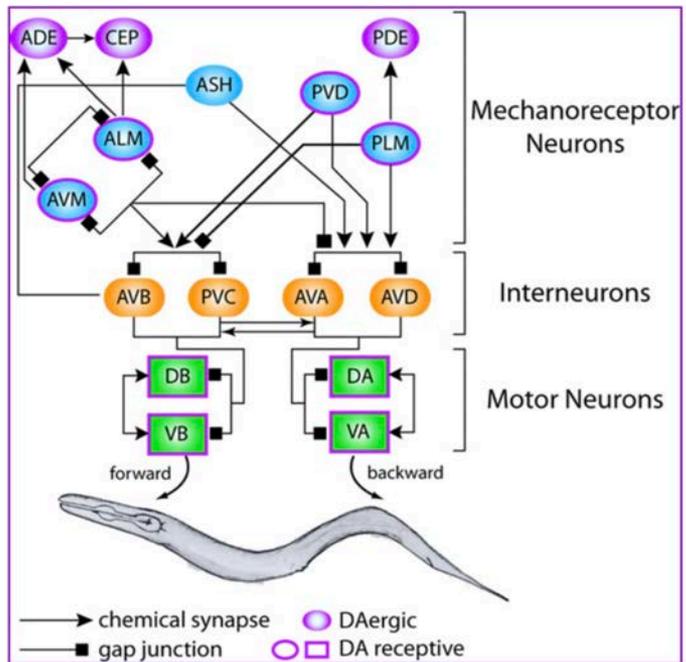


Diagram © Jeff Dean (adapted from DiCarlo & Cox, 2007). All rights reserved. This content is excluded from our Creative Commons License. For more information see <https://ocw.mit.edu/help/faq-fair-use/>.

# New technologies for neuronal activity measurements

*Video*

YaleCampus. "[Imaging Brain Activity Across the Mouse Cortex.](#)" YouTube.

# What is neural computation?

- Brain and cognitive sciences are no longer primarily descriptive
  - Engineering-level descriptions of brain systems.
- Use mathematical techniques to analyze neural data in a way that allows us to relate it to mathematical models.
- In this course we will have the added component that we will apply these techniques to understand the circuits and computational principles that underlie animal behavior.

# Neural circuits that control bird song

See Lecture 1 video recording for playback

# What is neural computation?

- Computational and quantitative approaches are also important in cognitive science.
- Importance of computation and quantitation in medical sciences

# Course Goals

- Understand the basic biophysics of neurons and networks and other principles underlying brain and cognitive functions
- Use mathematical techniques to
  - analyze simple models of neurons and networks
  - do data analysis of behavioral and neuronal data (compact representation of data)
- Become proficient at using numerical methods to implement these techniques (MATLAB<sup>®</sup>)

# Topics

|   |                                       |
|---|---------------------------------------|
| Neuronal biophysics and model neurons   | Differential equations                |
| Neuronal responses and tuning curves    | Spike sorting, PSTHs and firing rates |
| Neural coding and receptive fields      | Correlation and convolution           |
| Feed forward networks and perceptrons   | Linear algebra                        |
| Data analysis, dimensionality reduction | Principle Component Analysis and SVD  |
| Short-term memory, decision making      | Recurrent networks, eigenvalues       |
| Sensory integration                     | Bayes rule                            |

# Skills you will have

- Translate a simple model of neurons and neural circuits into a mathematical model
- Be able to simulate simple models using MATLAB®
- Be able to analyze neuronal data (or model output) using MATLAB®
- Be able to visualize high dimensional data.
- Be able to productively contribute to research in a neuroscience lab!

# Problem sets

- MATLAB<sup>®</sup> will be used extensively for the problem sets.
  - Free for students. Please install on your laptop.
- We will use live scripts for Pset submissions.

# Introduction to Neural Computation

---

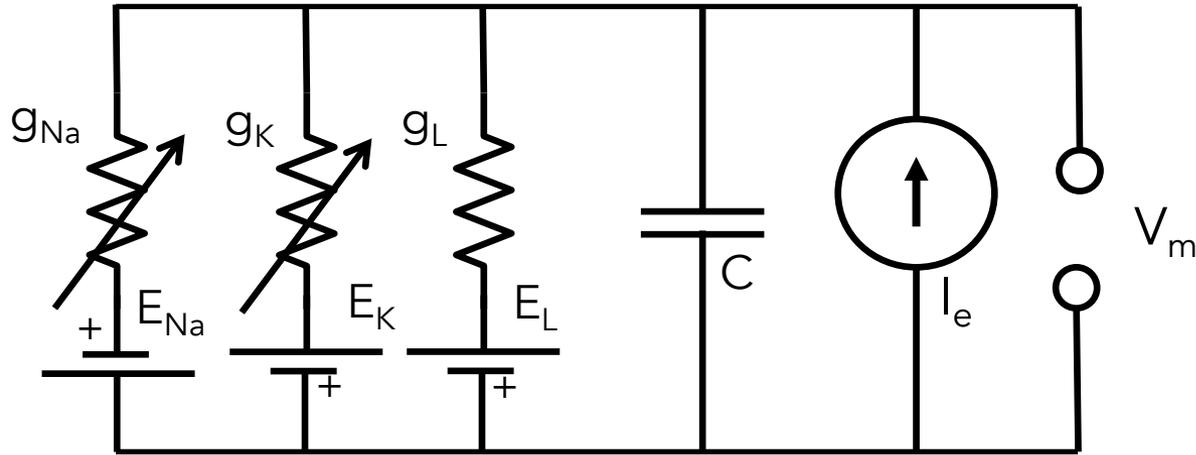
Michale Fee

MIT BCS 9.40 — 2018

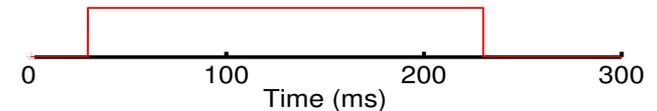
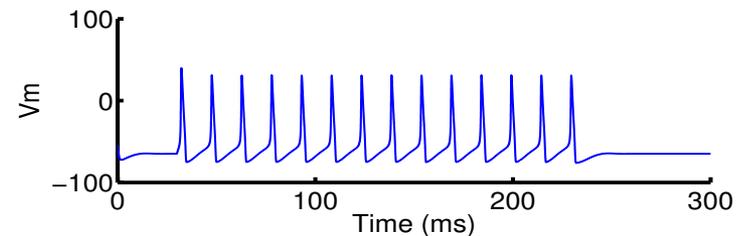
Lecture 1 – Ionic Currents

# A mathematical model of a neuron

- Equivalent circuit model



- A conceptual model based on simple components from electrical circuits
- A mathematical model that we can use to calculate properties of neurons



# Why build a model of a neuron?

- Neurons are very complex.
- Different neuron types are defined by the genes that are expressed and their complement of ion channels
- Ion channels have dynamics at different timescales, voltage ranges, inactivation

Figures removed due to copyright restrictions. Left side is Figure 3a: Spectral tSNE plot of 13,079 neurons, colored according to the results of iterative subclustering. Campbell, J., et al. "[A molecular census of arcuate hypothalamus and median eminence cell types.](#)" Nature Neuroscience 20, pages 484–496 (2017). Right side is Figure 1: Representation of the amino acid sequence relations of the minimal pore regions of the voltage-gated ion channel superfamily. Yu, F.H. and W.A. Catterall. "[The VGL-Chanome: A Protein Superfamily Specialized for Electrical Signaling and Ionic Homeostasis.](#)" Science's STKE05 Oct 2004: re15.

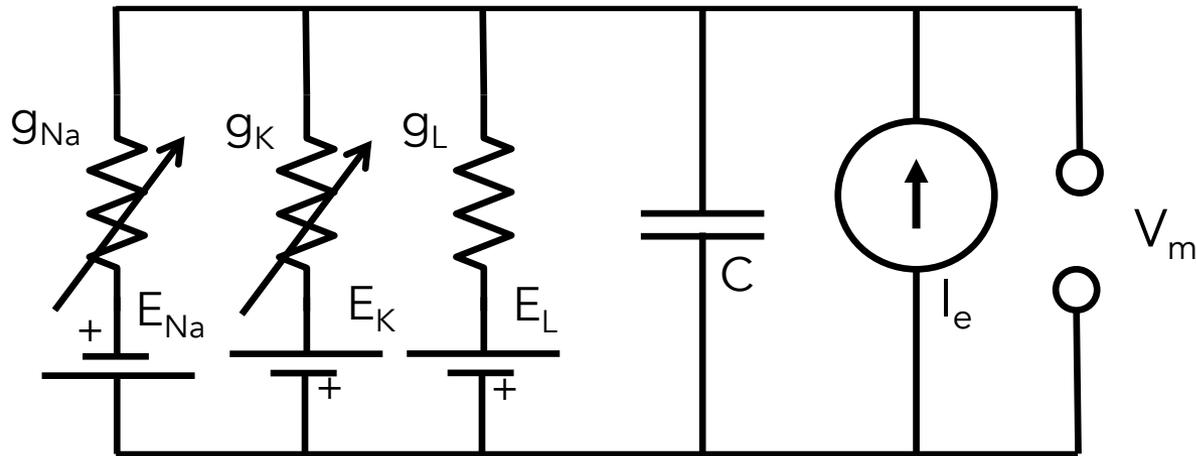
# Neurons are extremely complex

- Ion channel and morphological diversity lead to diversity of firing patterns
- It's hard to guess how morphology and ion channels lead to firing patterns
- ... and how firing patterns control circuit behavior

Figures removed due to copyright restrictions. Left side source unknown. Right side is Figure 6.1: [Multiple firing patterns in cortical neurons](#). *In*: Gerstner, W., et al. Neuronal Dynamics. Cambridge University Press.

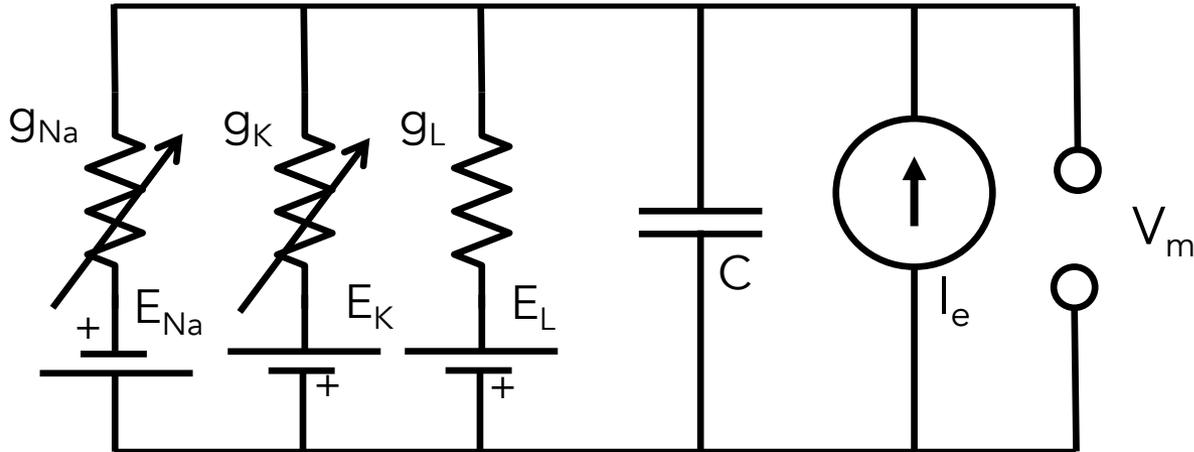
# A mathematical model of a neuron

- Equivalent circuit model



- Different parts of this circuit do different interesting things
  - Power supplies
  - Integrator of past inputs
  - Temporal filter to smooth inputs in time
  - Spike generator
  - Oscillator

# Ionic currents

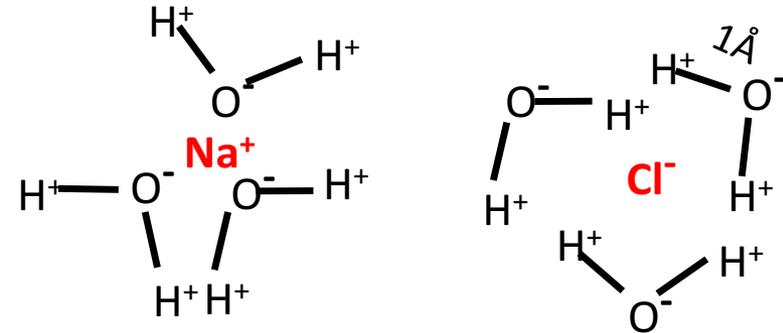


What are the wires of the brain?

In the brain (in neurons), current flow results from the movement of ions in aqueous solution (water).

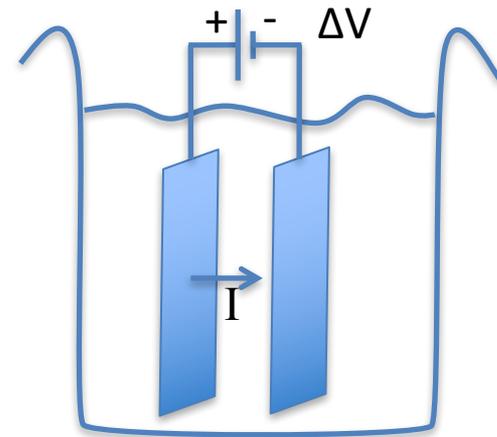
# Basic electrochemistry

- Water is a polar solvent
- Intracellular and extracellular space is filled with salt solution (~100mM)
  - $6 \times 10^{19}$  ions per  $\text{cm}^3$  (25Å spacing)



- Currents flow through a salt solution by two key mechanisms:

- Diffusion
- Drift in an electric field



# Learning objectives for Lecture 1

- To understand how the timescale of diffusion relates to length scales
- To understand how concentration gradients lead to currents (Fick's First Law)
- To understand how charge drift in an electric field leads to currents (Ohm's Law and resistivity)

# Thermal energy

- Every degree of freedom comes to thermal equilibrium with an energy proportional to temperature (Kelvin, K)

- The proportionality constant is the Boltzmann constant (k)

$$kT = 4 \times 10^{-21} \text{ Joules at } 300\text{K}$$

- Kinetic energy :  $\left\langle \frac{1}{2} m v_x^2 \right\rangle = \frac{1}{2} kT$        $\langle v_x^2 \rangle = \frac{kT}{m}$

- The mass of a sodium ion is  $3.8 \times 10^{-26}$  kg

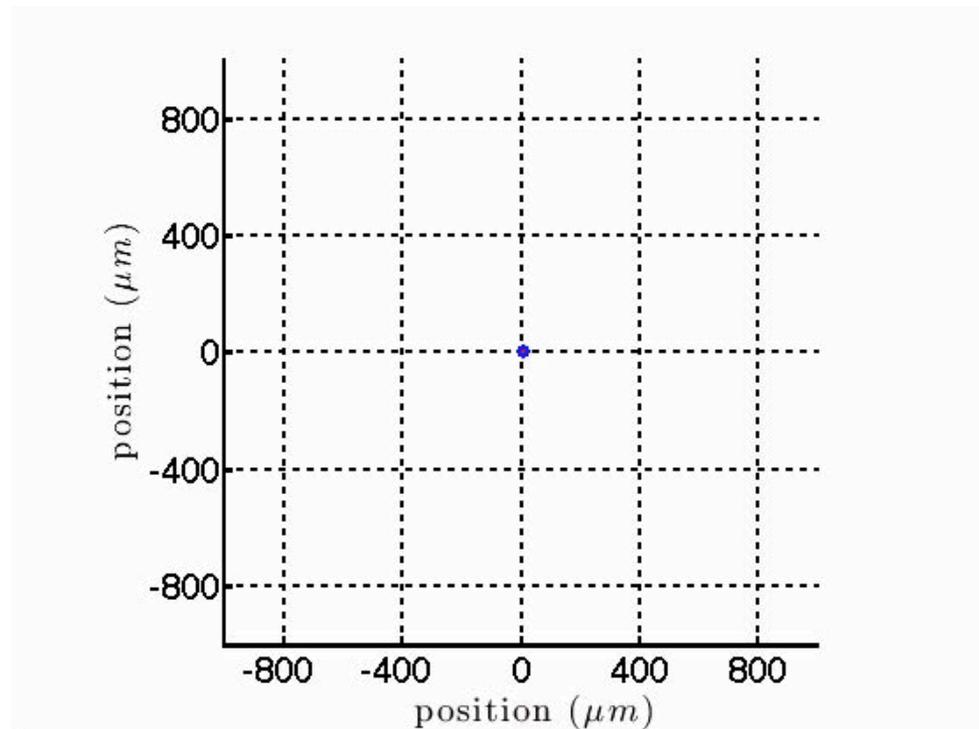
$$\langle v_x^2 \rangle = 10^5 \text{ m}^2 / \text{s}^2 \quad \Rightarrow \quad \bar{v}_x = 3.2 \times 10^2 \text{ m/s}$$

This would cross this 10m classroom in 3/10 second!

# What is diffusion?

- A particle in solution undergoes collisions with water molecules very often ( $\sim 10^{13}$  times per second!) that constantly change its direction of motion.

Collisions produce a 'random walk' in space



# Spatial and temporal scales

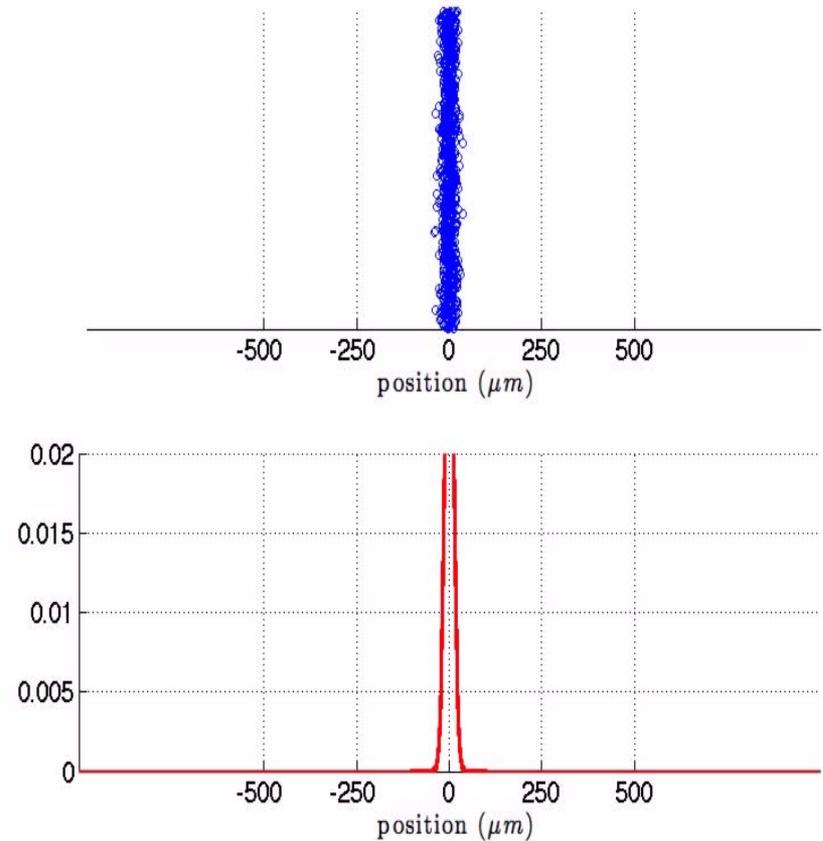
Diffusion is fast at short length scales and slow at long length scales.

- To diffuse across a cell body (10 $\mu$ m) it takes an ion 50ms
- To diffuse down a dendrite (1mm) it takes about 10min
- How long does it take an ion to diffuse down a motor neuron axon (1m)?

**10 years!**

# Distribution of particles resulting from diffusion in 1-D

- On average particles stay clustered around initial position
- Particles spread out around initial position
- We can compute analytically properties of this distribution!

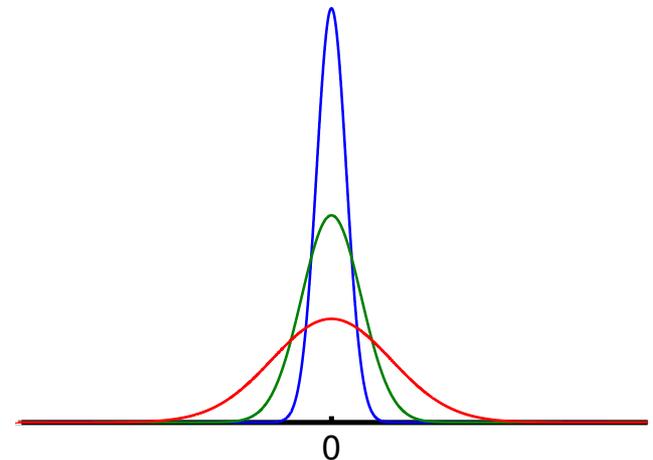


- An ensemble of particles diffusing from a point acquires a Gaussian distribution
- This arises from a binomial distribution for large number of time-steps (The probability of the particle moving exactly  $k$  steps to the right in  $n$  steps will be:

$$P(k;n,p) = \binom{n}{k} p^k (1-p)^{n-k}$$

$$\lim_{np \rightarrow \infty} P(k;n,p) = \frac{1}{\sqrt{4\pi Dt}} e^{-x^2/4Dt}$$

## Gaussian Distribution



# Random walk in one dimension

- We can mathematically analyze the properties of an ensemble of particles undergoing a random walk
- Consider a particle moving left or right at a fixed velocity  $v_x$  for a  $\mathcal{T}$  time before a collision.
- Imagine that each collision randomly resets the direction
- Thus, on every time-step,
  - half the particles step right by a distance  $\delta = +v_x \mathcal{T}$
  - and half the particles step to the left by a distance  $\delta$

# Random Walk in 1-D

- Assume that we have  $N$  particles that start at position  $x=0$  at time  $t=0$
- $x_i(n)$  = the position of the  $i^{\text{th}}$  particle on time-step  $n$ :  $n = t / \tau$
- Assume the movement of each particle is independent
- Thus, we can write the position of each particle at time-step  $n$  as a function of the position at previous time-step

$$x_i(n) = x_i(n-1) \pm \delta$$

- Use this to compute how the distribution evolves in time!

# Average displacement is zero

- What is the average position of our ensemble?

$$\langle x_i(n) \rangle_i = \frac{1}{N} \sum_i x_i(n) \quad x_i(n) = x_i(n-1) \pm \delta$$

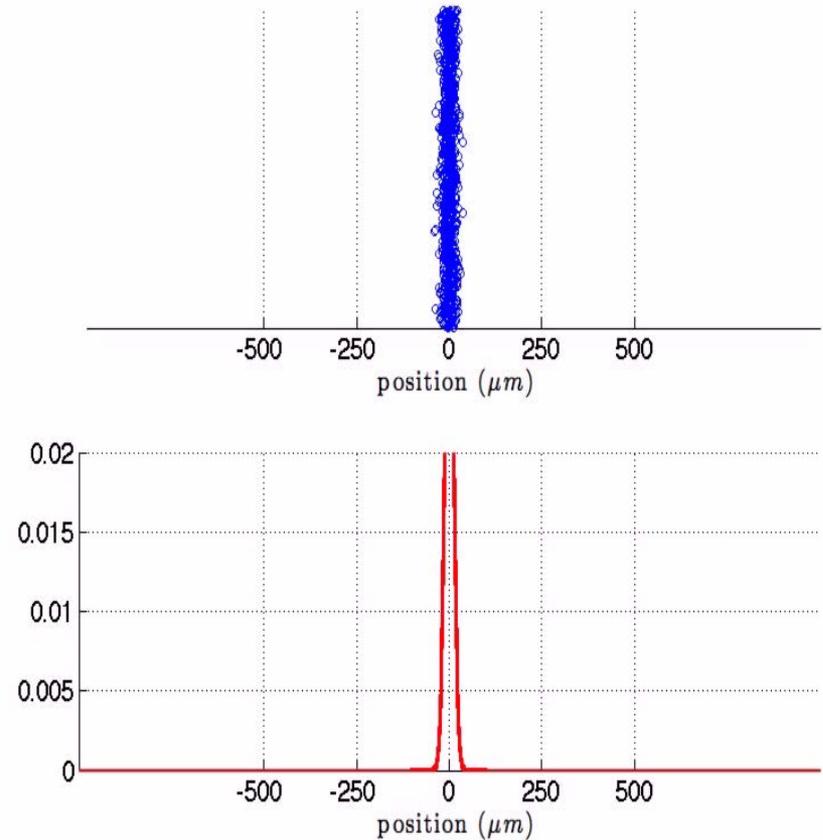
$$= \frac{1}{N} \sum_i [x_i(n-1) \pm \delta]$$

$$= \frac{1}{N} \sum_i [x_i(n-1)] + \frac{1}{N} \sum_i (\pm \delta)$$

$$\langle x_i(n) \rangle_i = \langle x_i(n-1) \rangle_i$$

# Distribution of particles resulting from diffusion in 1-D

- On average particles stay clustered around initial position
- Particles spread out around initial position
- We can compute analytically properties of this distribution!



# How far does a particle travel due to diffusion?

- We want to compute an average 'absolute value' distance from origin... Root mean square distance

$$\langle |x(n)| \rangle \rightarrow \sqrt{\langle x^2(n) \rangle}$$

Compute variance

$$x_i(n) = x_i(n-1) \pm \delta$$

$$x_i^2(n) = (x_i(n-1) \pm \delta)^2$$

$$= x_i^2(n-1) \pm 2\delta x_i(n-1) + \delta^2$$

$$\langle x^2(n) \rangle = \frac{1}{N} \sum_i x_i^2(n)$$

$$\langle x^2(n) \rangle = \langle x^2(n-1) \rangle + \langle \pm 2\delta x_i(n-1) \rangle + \langle \delta^2 \rangle$$

$$\langle x^2(n) \rangle = \langle x^2(n-1) \rangle + \delta^2$$

# How far does a particle travel due to diffusion?

$$\langle x^2(n) \rangle = \langle x^2(n-1) \rangle + \delta^2$$

- Note that at each time-step, the variance grows by  $\delta^2$

$$\langle x^2(0) \rangle = 0 \quad , \quad \langle x^2(1) \rangle = \delta^2 \quad , \quad \langle x^2(2) \rangle = 2\delta^2 \quad , \dots \quad \langle x^2(n) \rangle = n\delta^2$$

$$\langle x_i^2(t) \rangle = \frac{\delta^2 t}{\tau}, \quad n = t / \tau$$

$$\langle x_i^2 \rangle = 2Dt, \quad D = \delta^2 / 2\tau \quad (\text{Diffusion coefficient})$$

$$\sqrt{\langle x^2 \rangle} = \sqrt{2Dt}$$

# Spatial and temporal scales

$$L = \sqrt{2Dt} \quad L^2 = 2Dt \quad t = L^2/2D$$

Diffusion is fast at short length scales and slow at long length scales. Typical diffusion constants for small molecules and ions are  $\sim 10^{-5}$  cm<sup>2</sup>/s

- $L = 10\mu\text{m} = 10^{-3}$  cm       $t = 10^{-6}(\text{cm}^2)/2 \times 10^{-5}(\text{cm}^2/\text{s}) = 50$  ms
- $L = 1\text{mm} = 10^{-1}$  cm       $t = 10^{-2}(\text{cm}^2)/2 \times 10^{-5}(\text{cm}^2/\text{s}) = 500$  s
- $L = 1000\text{mm} = 10^2$  cm       $t = 10^4(\text{cm}^2)/2 \times 10^{-5}(\text{cm}^2/\text{s}) =$

500,000,000 seconds!!

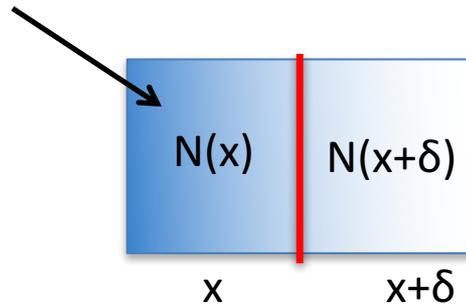
# Fick's first law

- Diffusion produces a net flow of particles from regions of high concentration to regions of lower concentration.
- The flux of particles is proportional to the concentration gradient.

$N(x)$  is the number of particles in the box at position  $x$

$$J_x = -D \frac{1}{\delta} [\varphi(x + \delta) - \varphi(x)]$$

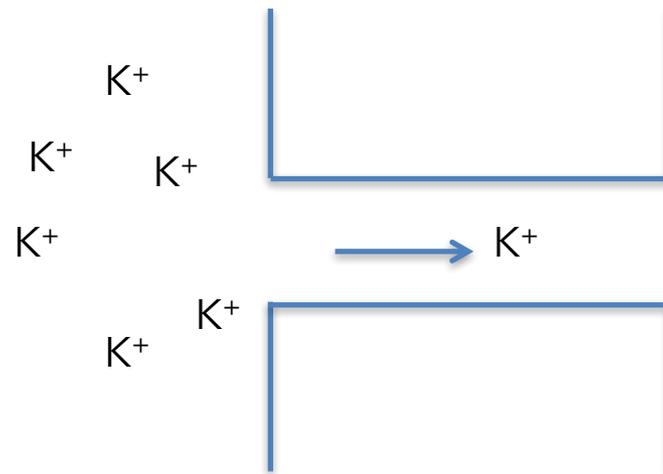
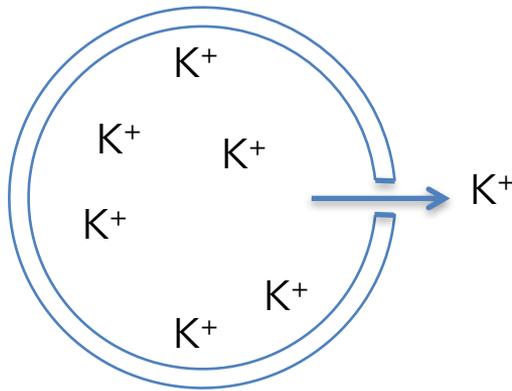
$$J_x = -D \frac{\partial \varphi}{\partial x}$$



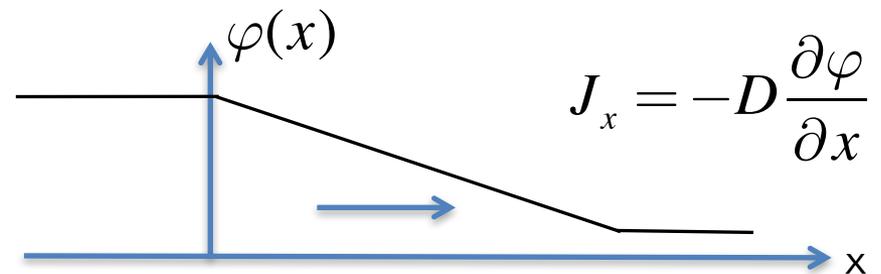
$$\frac{1}{2} N(x + \delta) \leftarrow \rightarrow \frac{1}{2} N(x)$$

$\frac{1}{2} [N(x) - N(x + \delta)]$  is the net number of particles moving to the right in an interval of time  $\tau$

# Diffusion produces a net flux of particles down a gradient



- Each particle diffuses independently and randomly!
- And yet concentration gradients produce currents!
- Eventually all concentration gradients go away...

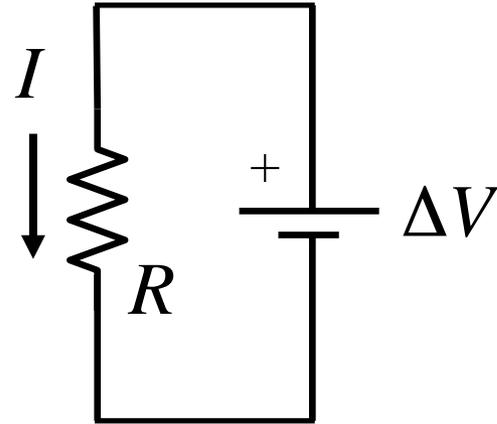


# Current flow in neurons obeys Ohm's Law

In a wire, current flow is proportional to voltage difference

Ohm's Law

$$I = \frac{\Delta V}{R}$$



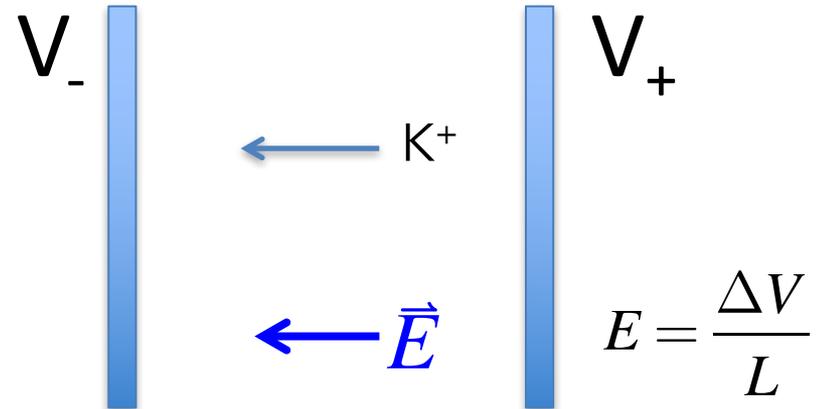
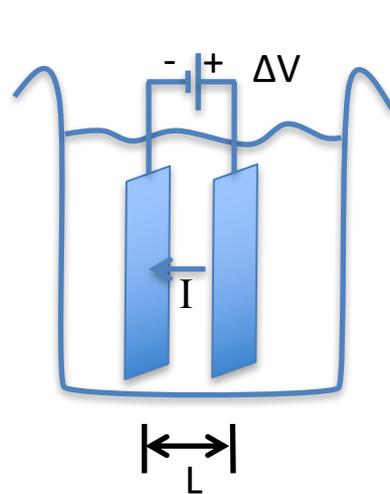
where

- $I$  is current (Amperes, A)
- $\Delta V$  is voltage (Volts, V)
- $R$  is resistance (Ohms,  $\Omega$ )

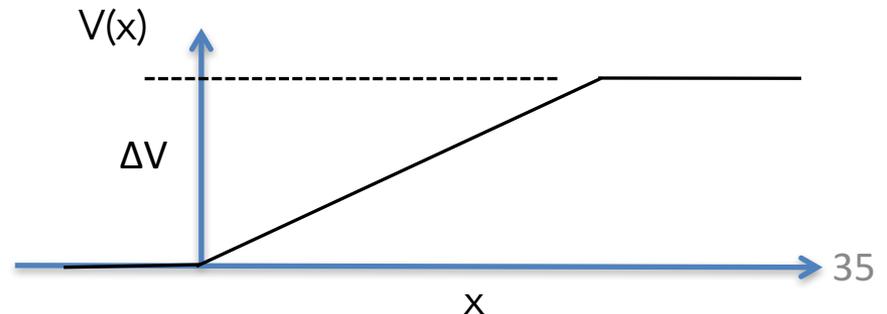
# Where does Ohm's Law come from?

Consider a beaker filled with salt solution, two electrodes, and a battery that produces a voltage difference between the electrodes.

- The electric field produces a force which, in a solution, causes an ion to drift with a constant velocity — a current



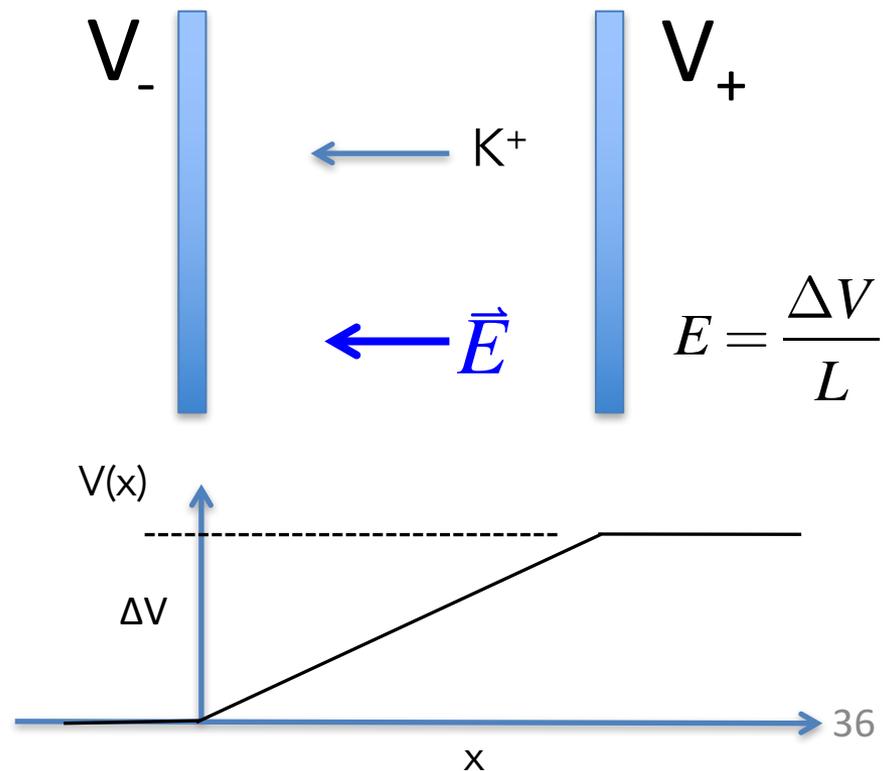
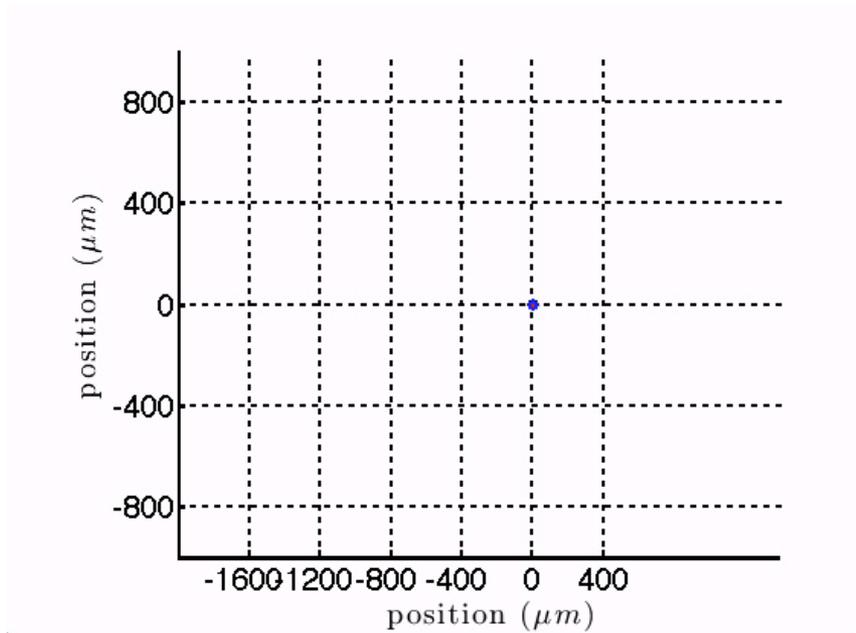
- Force:  $\vec{F} = q\vec{E}$



# Ion currents in an electric field

Currents are also caused by the drift of ions in the presence of an electric field.

- The electric field produces a force which, in a solution, causes an ion to drift with a constant velocity — a current



- Why constant velocity?

# Ion currents in an electric field

Currents are also caused by the drift of ions in the presence of an electric field.

- Einstein realized that this is just a result of viscous drag (or friction)

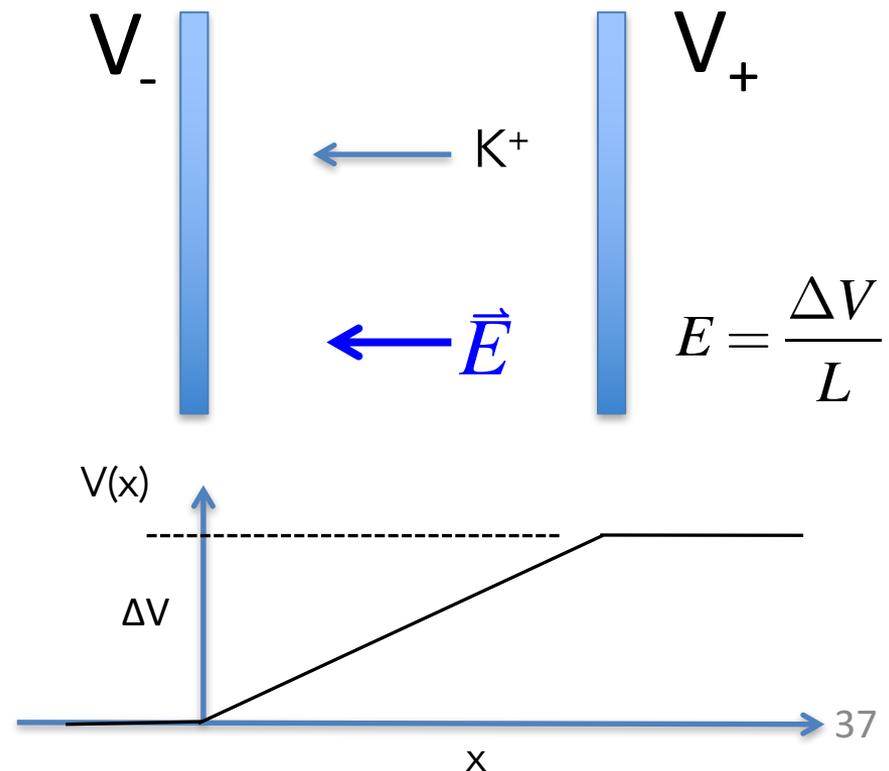
$$\vec{F} = f \vec{v}_d$$

- Einstein –Smoluchovski relation

$$f = kT / D$$

- Drift velocity is given by

$$\vec{v}_d = \frac{D}{kT} \vec{F} = \frac{D}{kT} (q\vec{E})$$



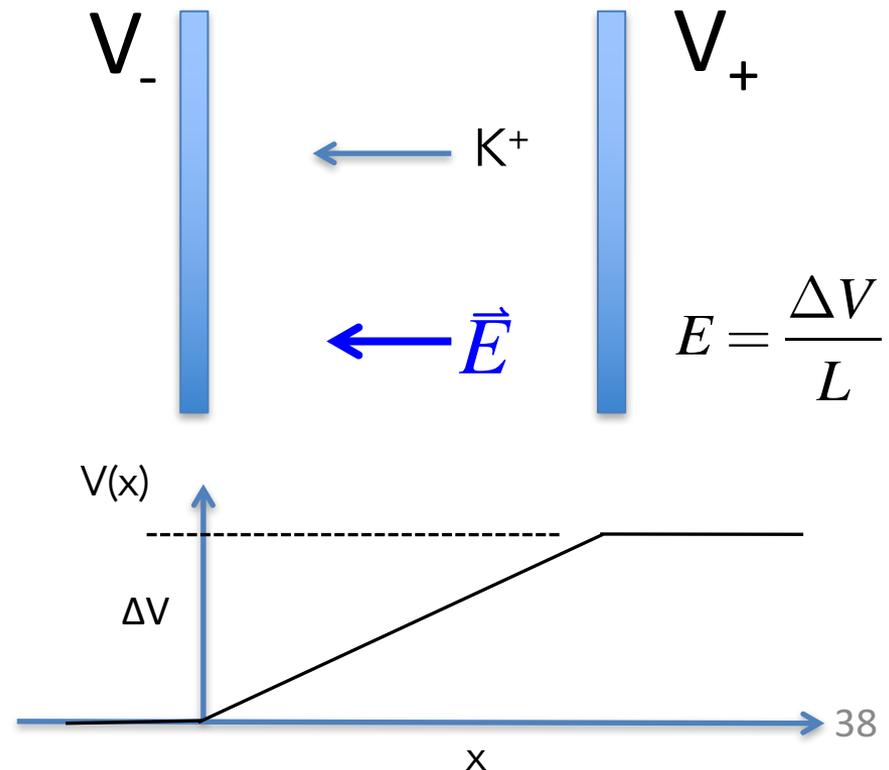
# Ion currents in an electric field

Currents are also caused by the drift of ions in the presence of an electric field.

- The electric field produces a force which, in a solution, causes an ion to drift with a constant velocity — a current

$$I \propto v_d A$$

$$I \propto E A = \frac{\Delta V}{L} A$$



# Ohm's Law in solution

In a solution, current flow per unit area is proportional to voltage gradients

$$I = \left( \frac{1}{\rho} \right) \frac{\Delta V}{L} A$$

$\rho$  = resistivity ( $\Omega \cdot \text{m}$ )

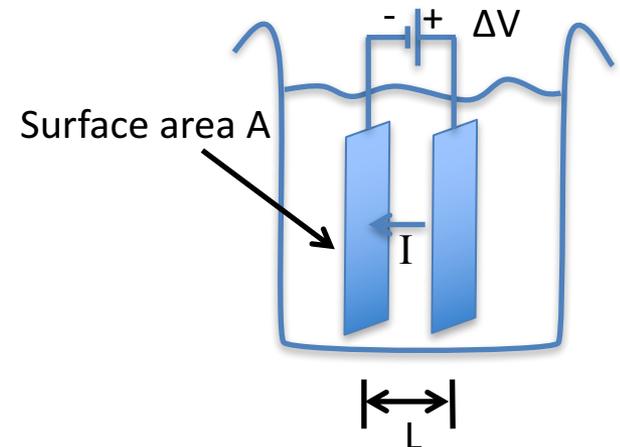
$$I = \frac{1}{R} \Delta V$$

- Let's make this look more like Ohm's Law

$$I = \left( \frac{A}{\rho L} \right) \Delta V$$

- Thus the resistance is given by:

$$R = \frac{\rho L}{A}$$

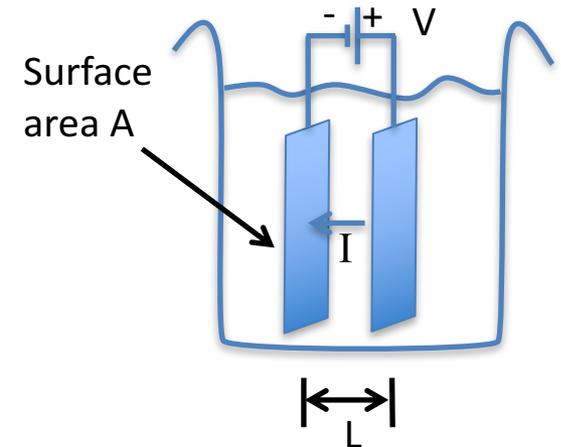


# Resistivity of intra/extra cellular space

- Resistance of a volume of conductive medium is given by

$$R = \frac{\rho L}{A}$$

- $\rho = 1.6 \mu\Omega \cdot \text{cm}$  for copper
- $\rho = \sim 60 \Omega \cdot \text{cm}$  for mammalian saline – the brain has lousy conductors!
- The brain has many specializations to deal with lousy wires...



# Learning objectives for Lecture 1

- To understand how the timescale of diffusion relates to length scales
  - Distance diffused grows as the square root of time
- To understand how concentration gradients lead to currents (Fick's First Law)
  - Concentration differences lead to particle flux, proportional to gradient
- To understand how charge drift in an electric field leads to currents (Ohm's Law and resistivity)

# (Extra slide) Derivation of resistivity

Current density (Coulombs per second per unit area) is just drift velocity times the density of ions times the charge per ion.

$$\frac{I}{A} = q\varphi v_d$$

$$\begin{aligned} \varphi &= \text{ion density (ions per m}^3\text{)} \\ q = ze &= \text{ionic charge (Coulombs per ion)} \\ &= \text{ion valence times } 1.6 \times 10^{-19} \text{ Coulombs} \end{aligned}$$

- Plugging in drift velocity from above, we get:

$$\frac{I}{A} = q\varphi \frac{D}{kT} (qE)$$

# Derivation of resistivity

- Thus, the current density (coulombs per second per unit area) is just proportional to the electric field:

$$\frac{I}{A} = \frac{q^2 \varphi D}{kT} E \qquad \frac{I}{A} = \left( \frac{1}{\rho} \right) E$$

- Solving for  $\rho$  we get:

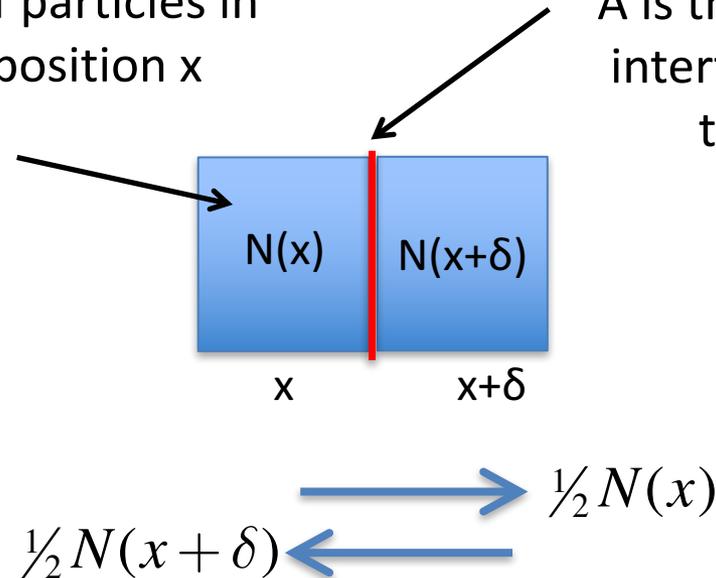
$$\rho = \frac{kT}{q^2 \varphi D} = \text{resistivity } (\Omega \cdot \text{m})$$

# Extra slides on derivation of Fick's first law

We will now use a similar approach to derive a macroscopic description of diffusion – a differential equation that describes the the flux of particles from the spatial distribution of their concentration.

$N(x)$  is the number of particles in a box (of length  $\delta$ ) at position  $x$

$A$  is the area of the interface between the boxes

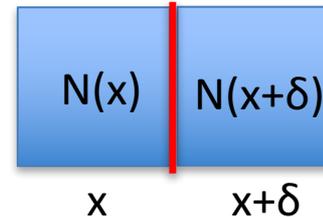


$\frac{1}{2}[N(x) - N(x + \delta)]$  is the net number of particles moving to the right in an interval of time  $\tau$

# Extra slides on derivation of Fick's first law

We can calculate the flux in units of particles per second per area

$$J_x = -\frac{1}{A\tau} \frac{1}{2} [N(x+\delta) - N(x)]$$



multiply by  $\delta^2 / \delta^2$

$$J_x = -\frac{\delta^2}{2\tau} \frac{1}{\delta} \left[ \frac{N(x+\delta)}{A\delta} - \frac{N(x)}{A\delta} \right]$$

Particles per unit volume

$$J_x = -D \frac{1}{\delta} [\varphi(x+\delta) - \varphi(x)]$$

Density - particles per unit volume

$$J_x = -D \frac{\partial \varphi}{\partial x}$$

Note: To get density (ions/m<sup>3</sup>) from molar concentration (mol/L), you have to multiply by  $N_A \times 10^{-3}$ . ( $N_A$  is Avagadro's Number =  $6.02 \times 10^{23}$ )

MIT OpenCourseWare  
<https://ocw.mit.edu/>

9.40 Introduction to Neural Computation  
Spring 2018

For information about citing these materials or our Terms of Use, visit: <https://ocw.mit.edu/terms>.