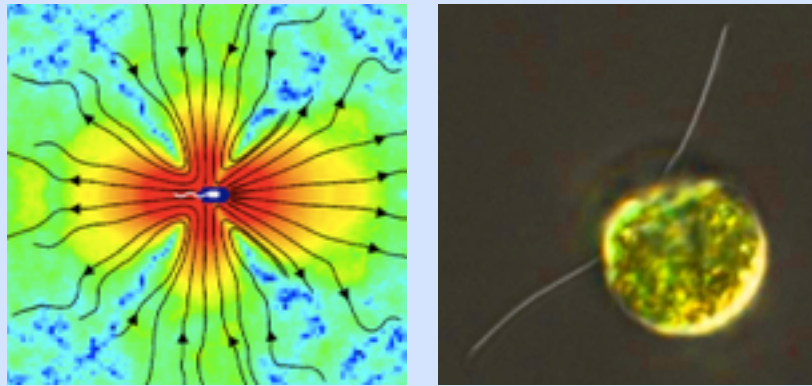


18.095 IAP Maths Lecture Series

Over-damped dynamics of small objects in fluids

Jörn Dunkel
Physical Applied Math

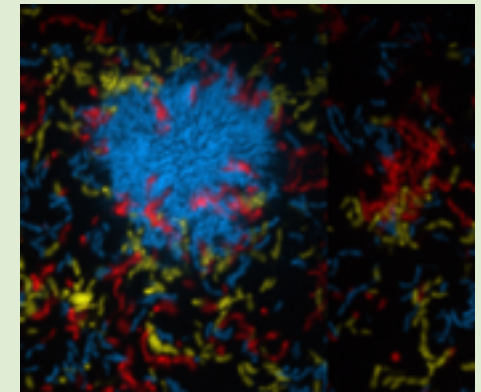
Fluid dynamics of microorganisms



Goldstein group



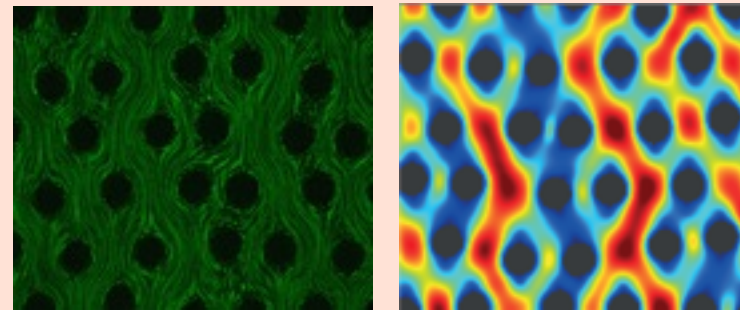
Biofilm formation



Drescher lab



Microbial transport in porous media



Guasto lab

Surface wrinkling



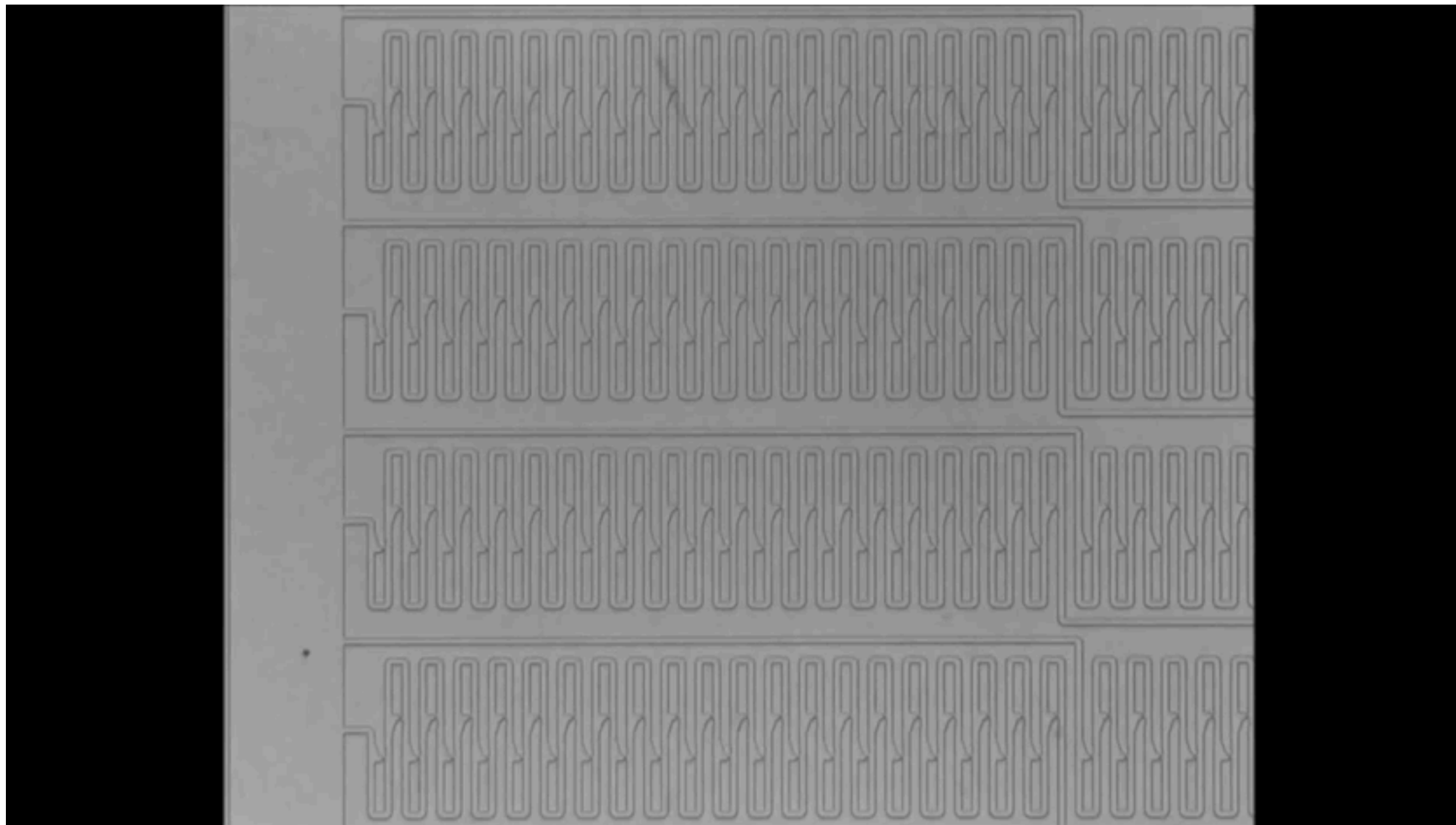
Reis lab

Biological pattern formation



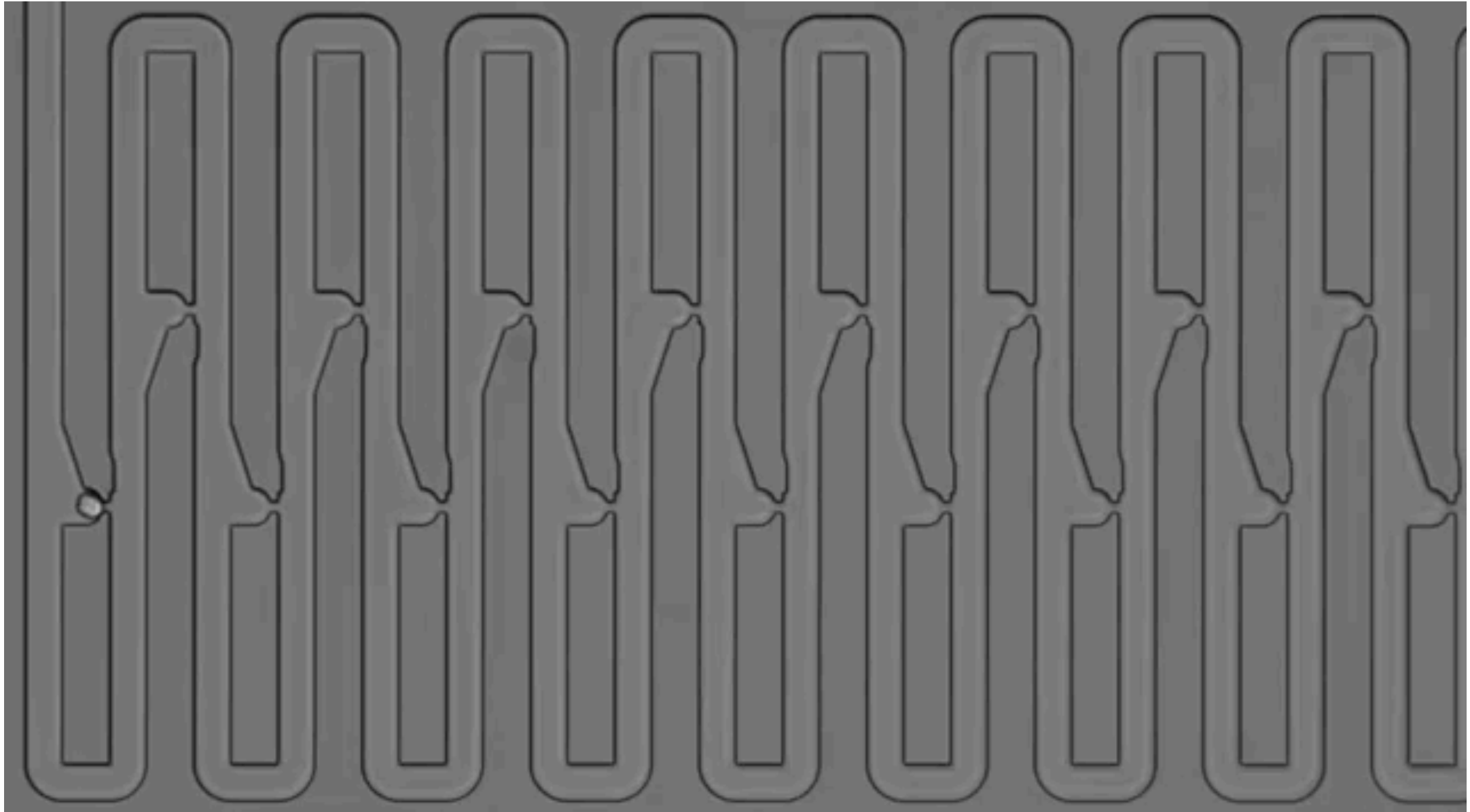
Gregor lab





Labs of Manalis & Shalek

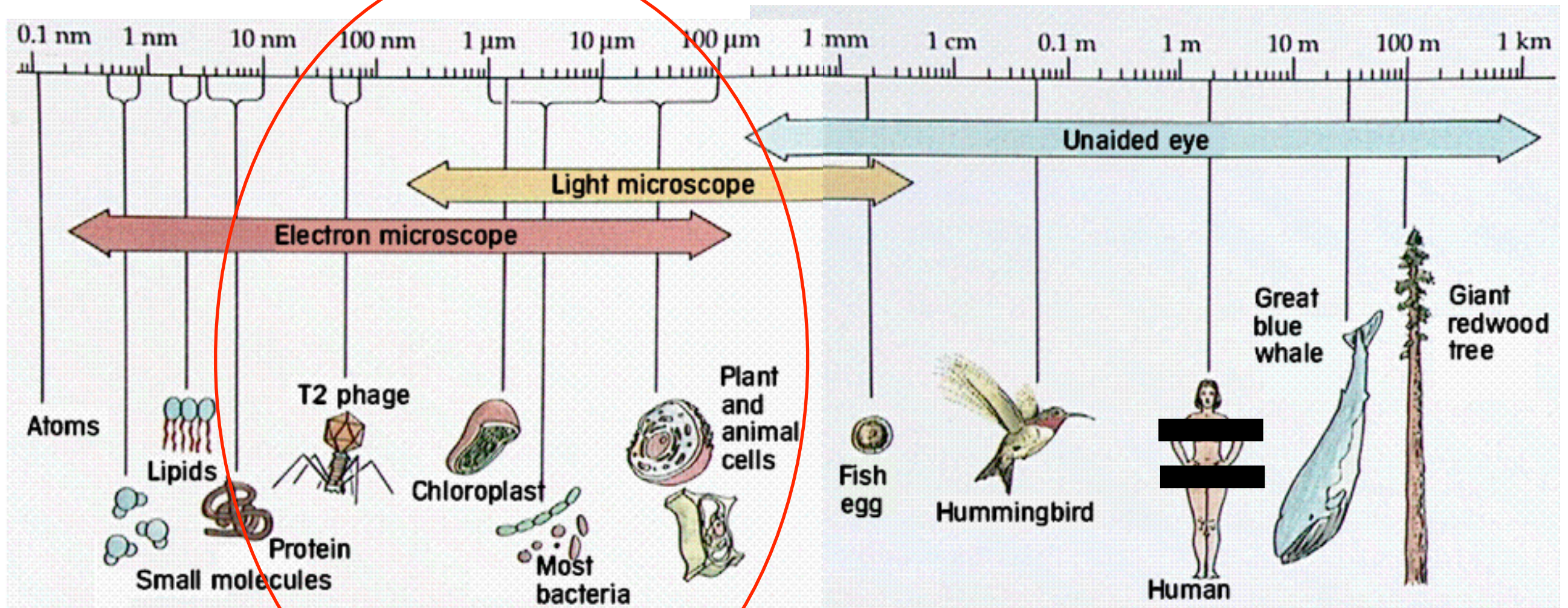
Nature Communications **7**, Article number: 10220



Labs of Manalis & Shalek

Nature Communications **7**, Article number: 10220

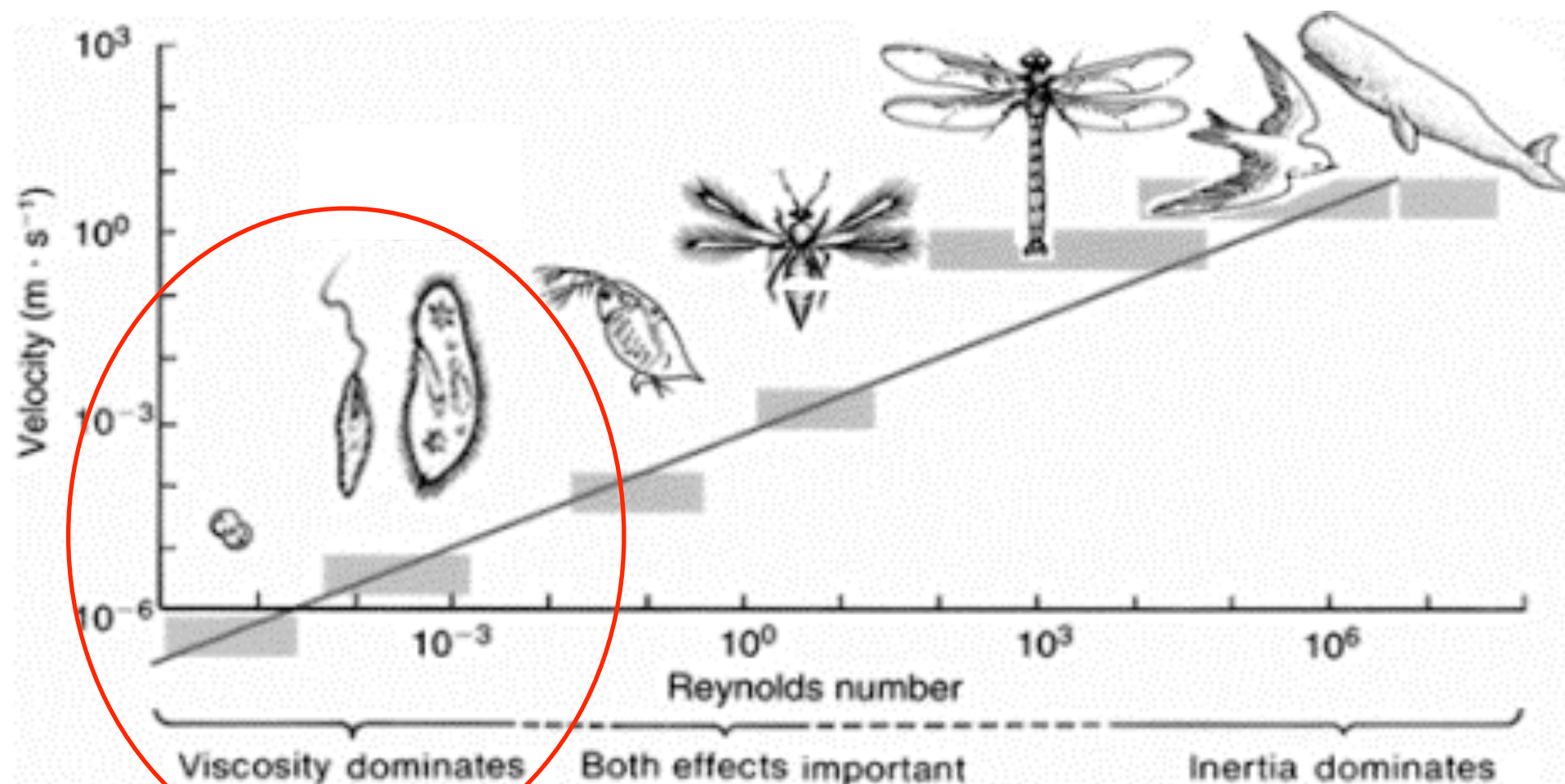
Typical length scales



<http://www2.estrellamountain.edu/faculty/farabee/BIOBK/biobookcell2.html>

Reynolds numbers

$$Re = \frac{\rho U L}{\mu} = \frac{U L}{\nu}$$



Laminar (low-Re) flow



For $Re \rightarrow 0$
fluid flow becomes
reversible !

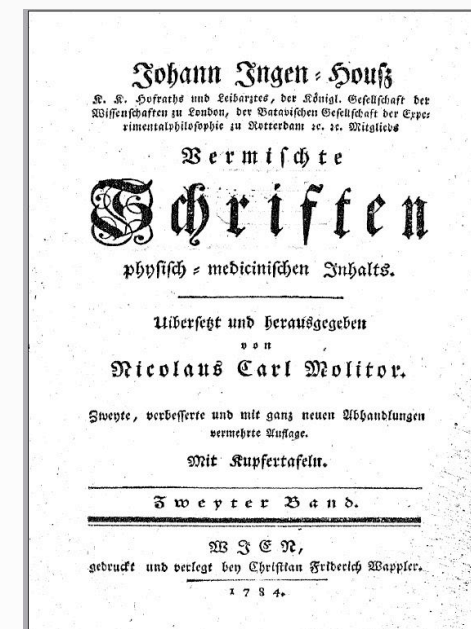
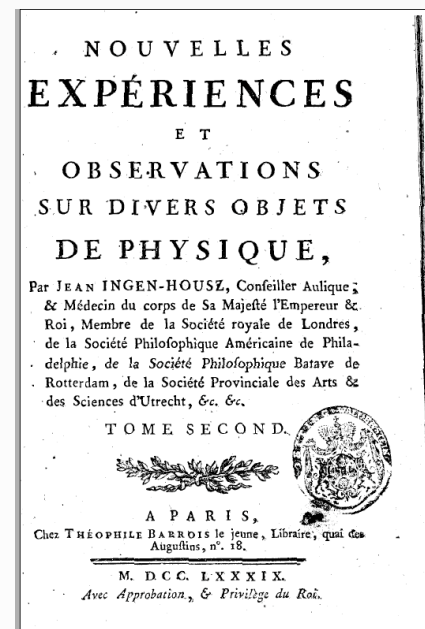
... except for thermal
fluctuations

Brownian motion



“Brownian” motion

Jan Ingen-Housz (1730-1799)



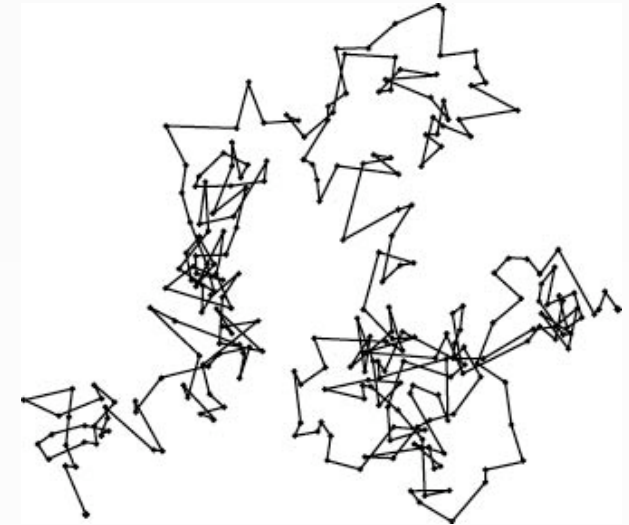
1784/1785:

über betrügen könnte, darf man nur in den Brennpunct eines Mikroskops einen Tropfen Weingeist sammt etwas gestoßener Kohle setzen; man wird diese Körperchen in einer verwirrten beständigen und heftigen Bewegung erblicken, als wenn es Thierchen wären, die sich reißend unter einander fortbewegen.

Robert Brown (1773-1858)



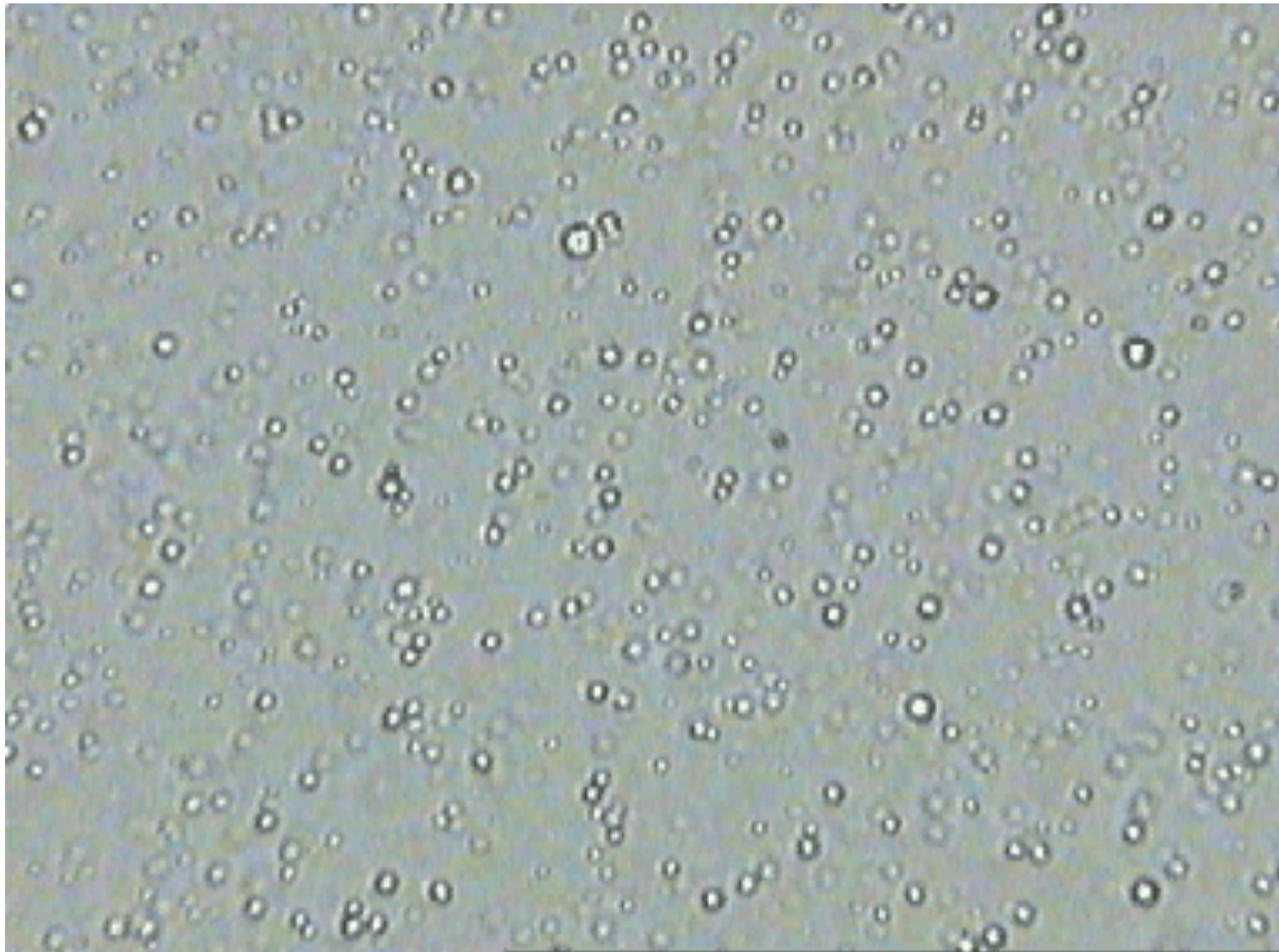
Linnean Society (London)



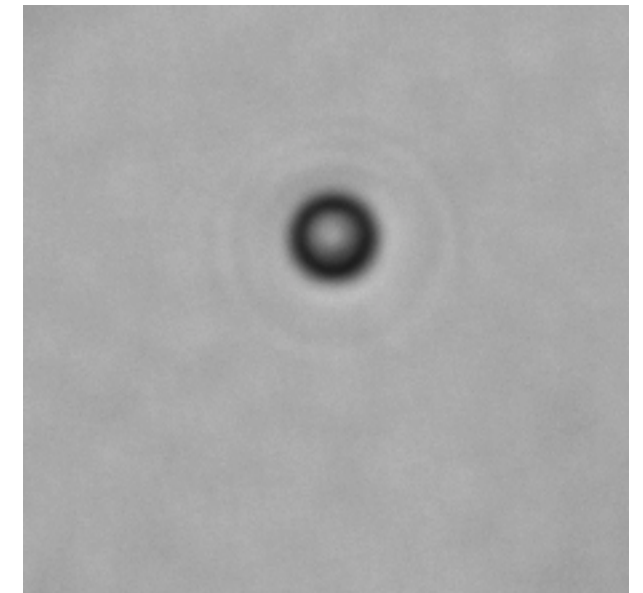
1827: irregular motion of pollen in fluid

<http://www.brianjford.com/wbbrownc.htm>

Brownian motion



David Walker



Mark Haw

W. Sutherland (1858-1911)

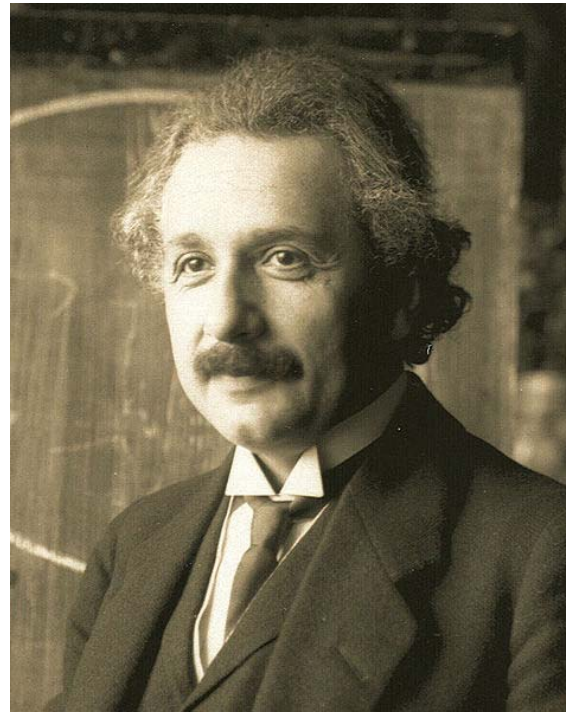


Source: www.theage.com.au

$$D = \frac{RT}{6\pi\eta aC}$$

Phil. Mag. **9**, 781 (1905)

A. Einstein (1879-1955)



Source: wikipedia.org

$$\langle x^2(t) \rangle = 2Dt$$
$$D = \frac{RT}{N} \frac{1}{6\pi kP}$$

Ann. Phys. **17**, 549 (1905)

M. Smoluchowski
(1872-1917)

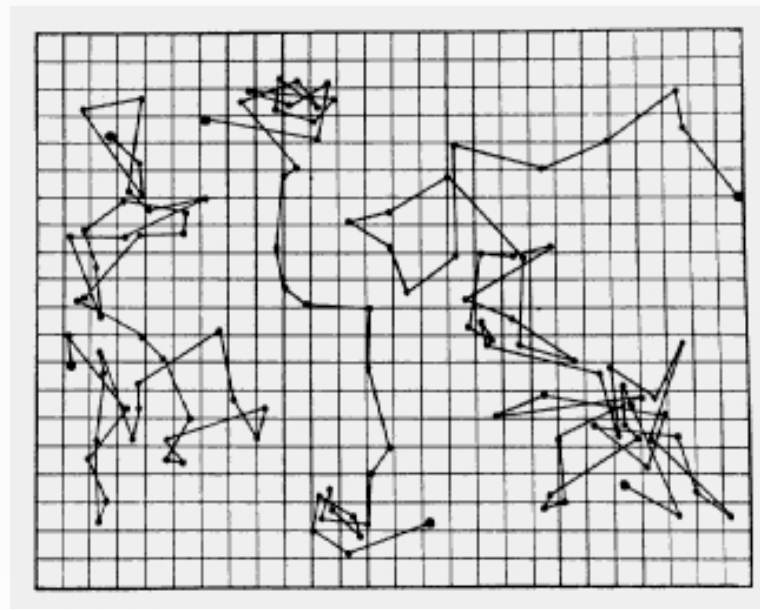
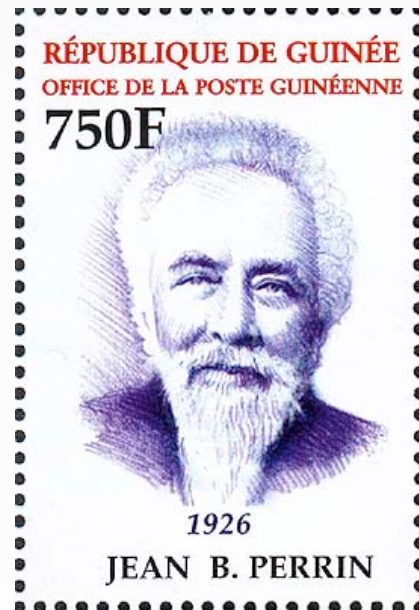


Source: wikipedia.org

$$D = \frac{32}{243} \frac{mc^2}{\pi\mu R}$$

Ann. Phys. **21**, 756 (1906)

Jean Baptiste Perrin (1870-1942, Nobel prize 1926)



- ▶ colloidal particles of radius $0.53\mu\text{m}$
- ▶ successive positions every 30 seconds joined by straight line segments
- ▶ mesh size is $3.2\mu\text{m}$

Mouvement brownien et réalité moléculaire, Annales de chimie et de physique VIII 18, 5-114 (1909)

Les Atomes, Paris, Alcan (1913)

$$D = \frac{kT}{6\pi\eta_0 a}, \quad k = \frac{R}{N_A}$$

$$N_A = 6.56 \times 10^{23}$$

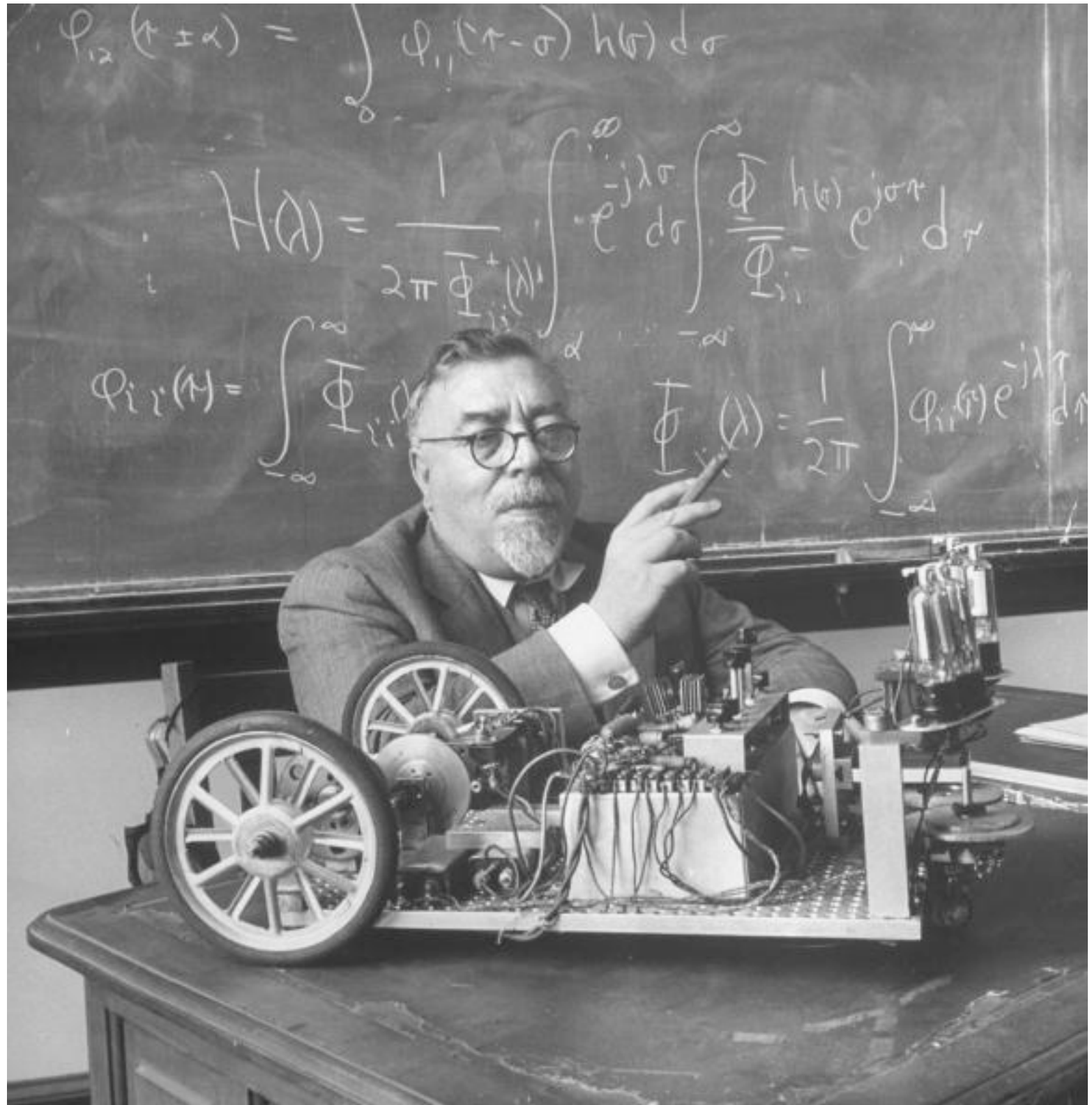
experimental evidence for
atomistic structure of matter

Mathematical theory

Norbert Wiener

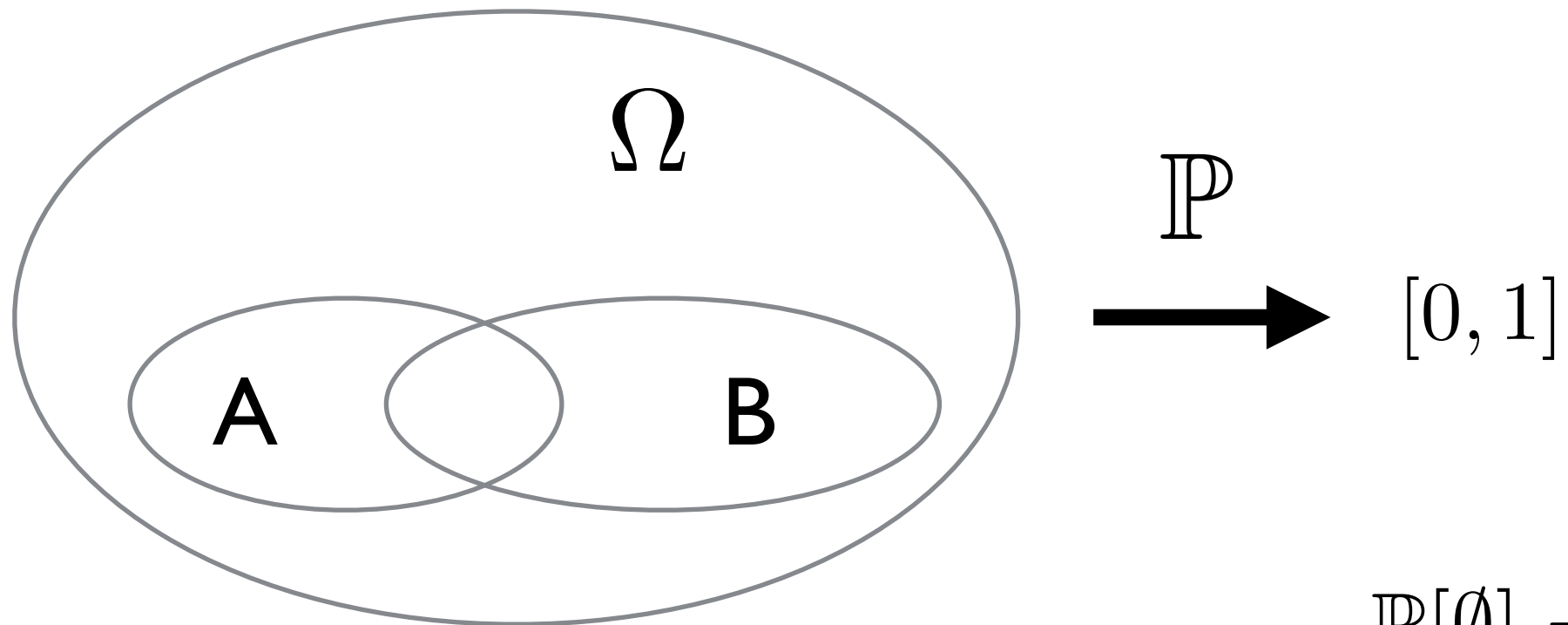
(1894-1964)

MIT



Probability space $(\Omega, \mathcal{F}, \mathbb{P})$

$$\mathcal{F} = \{\emptyset, A, B, A \cap B, A \cup B, \dots, \Omega\}$$



$$\mathbb{P}[\emptyset] = 0$$

$$\mathbb{P}[\Omega] = 1$$

$$\mathbb{P}[A \cup B] = \mathbb{P}[A] + \mathbb{P}[B] - \mathbb{P}[A \cap B]$$

Expectation values of **discrete** random variables

$$X : \Omega \rightarrow \{x_1, \dots, x_N\}$$

$$p_i \geq 0, \quad \sum_{i=1}^N p_i = 1$$

$$\mathbb{E}[f(X)] = \sum_{i=1}^N p_i f(x_i)$$

$$\mathbb{E}[\alpha f(X) + \beta g(X)] = \alpha \mathbb{E}[f(X)] + \beta \mathbb{E}[g(X)]$$

Expectation values of **continuous** random variables

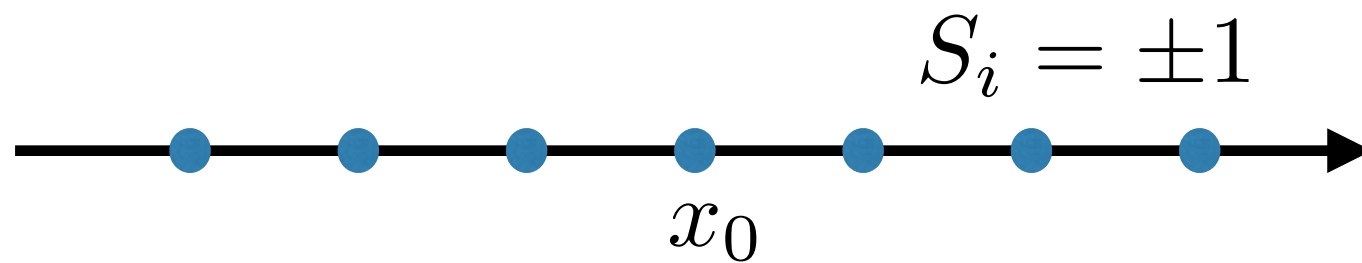
$$X : \Omega \rightarrow \mathbb{R}^n$$

$$p(x) \geq 0, \quad \int dx \, p(x) = 1$$

$$\mathbb{E}[f(X)] = \int d\mathbb{P} f(x) = \int dx \, p(x) f(x)$$

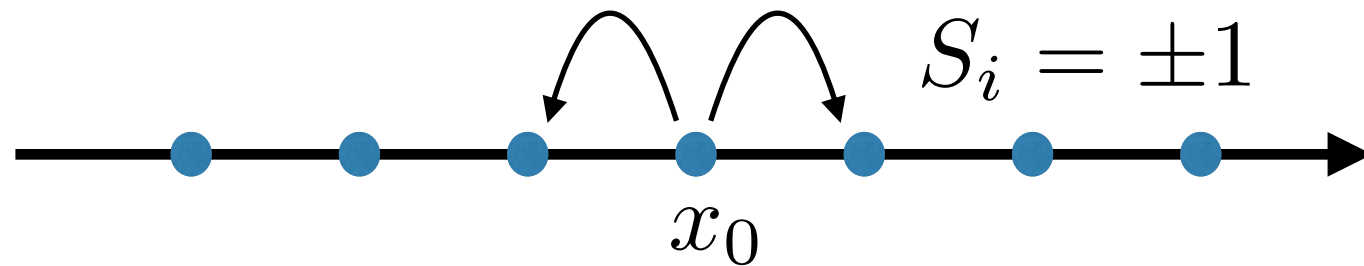
$$\mathbb{E}[\alpha f(X) + \beta g(X)] = \alpha \mathbb{E}[f(X)] + \beta \mathbb{E}[g(X)]$$

Random walk model



$$X_N = x_0 + \ell \sum_{i=1}^N S_i$$

$$\mathbb{E}[f(S)] = \sum_{a=1}^2 p_a f(s_a)$$



1.1 Random walk

Consider the one-dimensional unbiased RW (fixed initial position $X_0 = x_0$, N steps of length ℓ)

$$X_N = x_0 + \ell \sum_{i=1}^N S_i \quad (1.1)$$

where $S_i \in \{\pm 1\}$ are iid. random variables (RVs) with $\mathbb{P}[S_i = \pm 1] = 1/2$. Noting that ¹

$$\mathbb{E}[S_i] = -1 \cdot \frac{1}{2} + 1 \cdot \frac{1}{2} = 0, \quad (1.2)$$

$$\mathbb{E}[S_i S_j] = \delta_{ij} \mathbb{E}[S_i^2] = \delta_{ij} \left[(-1)^2 \cdot \frac{1}{2} + (1)^2 \cdot \frac{1}{2} \right] = \delta_{ij}, \quad (1.3)$$

we find for the first moment of the RW

$$\mathbb{E}[X_N] = x_0 + \ell \sum_{i=1}^N \mathbb{E}[S_i] = x_0 \quad (1.4)$$

Second moment (uncentered)

$$\begin{aligned}\mathbb{E}[X_N^2] &= \mathbb{E}\left[\left(x_0 + \ell \sum_{i=1}^N S_i\right)^2\right] \\ &= \mathbb{E}\left[x_0^2 + 2x_0\ell \sum_{i=1}^N S_i + \ell^2 \sum_{i=1}^N \sum_{j=1}^N S_i S_j\right] \\ &= x_0^2 + 2x_0 \cdot 0 + \ell^2 \sum_{i=1}^N \sum_{j=1}^N \mathbb{E}[S_i S_j] \\ &= x_0^2 + 2x_0 \cdot 0 + \ell^2 \sum_{i=1}^N \sum_{j=1}^N \delta_{ij} \\ &= x_0^2 + \ell^2 N.\end{aligned}\tag{1.5}$$

Variance


The variance (second centered moment)

$$\begin{aligned}\mathbb{E} [(X_N - \mathbb{E}[X_N])^2] &= \mathbb{E}[X_N^2 - 2X_N\mathbb{E}[X_N] + \mathbb{E}[X_N]^2] \\ &= \mathbb{E}[X_N^2] - 2\mathbb{E}[X_N]\mathbb{E}[X_N] + \mathbb{E}[X_N]^2 \\ &= \mathbb{E}[X_N^2] - \mathbb{E}[X_N]^2\end{aligned}\tag{1.6}$$

therefore grows linearly with the number of steps:

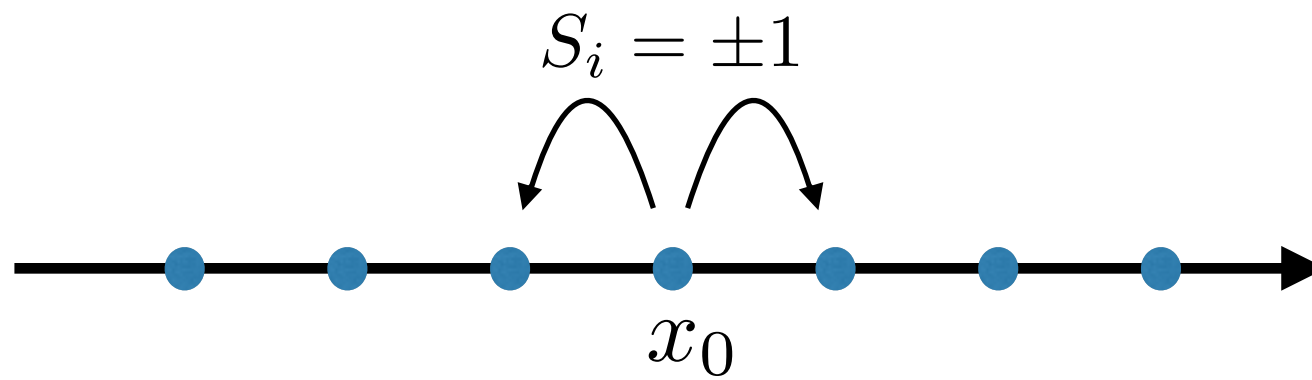
$$\mathbb{E} [(X_N - \mathbb{E}[X_N])^2] = \ell^2 N.\tag{1.7}$$

Let

$$x_0 = 0, \quad N = t/\tau$$


$$\mathbb{E}[X_N^2] = 2Dt, \quad D := \frac{\ell^2}{2\tau}$$

Continuum limit

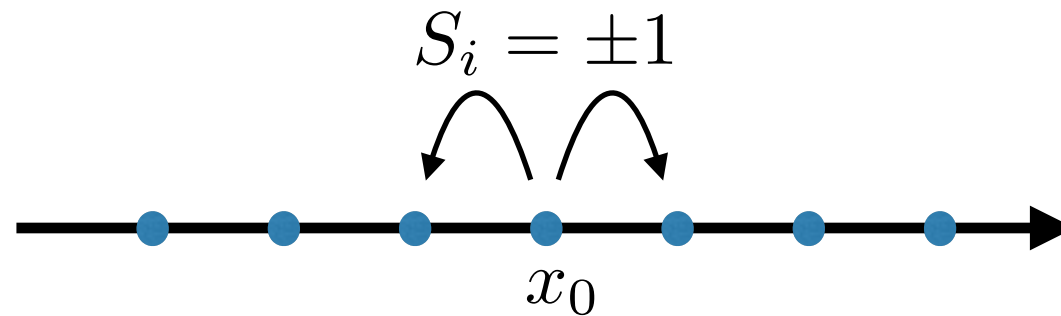


$$X_N = x_0 + \ell \sum_{i=1}^N S_i$$

Let $x_0 = 0, \quad N = t/\tau$

$$P(N, K) := \mathbb{P}[X_N/\ell = K]$$

Continuum limit



$$\begin{aligned}
 P(N, K) &= \left(\frac{1}{2}\right)^N \binom{N}{\frac{N-K}{2}} \\
 &= \left(\frac{1}{2}\right)^N \frac{N!}{((N+K)/2)! ((N-K)/2)!}.
 \end{aligned} \tag{1.8}$$

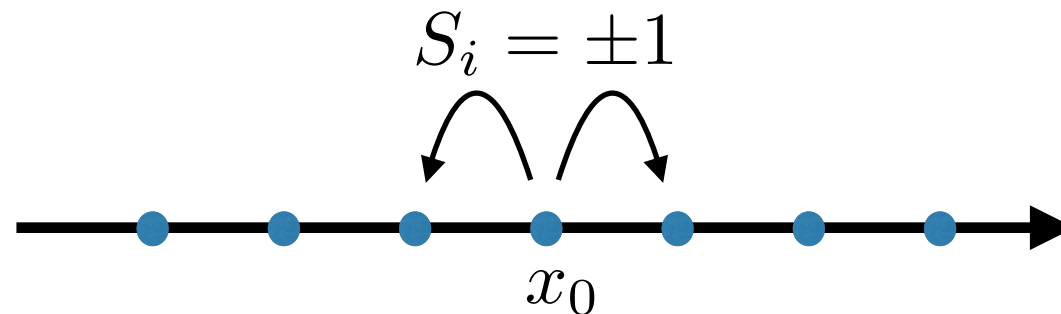
The associated probability density function (PDF) can be found by defining

$$p(t, x) := \frac{P(N, K)}{2\ell} = \frac{P(t/\tau, x/\ell)}{2\ell} \tag{1.9}$$

and considering limit $\tau, \ell \rightarrow 0$ such that

$$D := \frac{\ell^2}{2\tau} = \text{const}, \tag{1.10}$$

Continuum limit



yielding the Gaussian

$$p(t, x) \simeq \sqrt{\frac{1}{4\pi Dt}} \exp\left(-\frac{x^2}{4Dt}\right) \quad (1.11)$$

Eq. (1.11) is the fundamental solution to the diffusion equation,

$$\partial_t p_t = D \partial_{xx} p, \quad (1.12)$$

where $\partial_t, \partial_x, \partial_{xx}, \dots$ denote partial derivatives. The mean square displacement of the continuous process described by Eq. (1.11) is

$$\mathbb{E}[X(t)^2] = \int dx \, x^2 p(t, x) = 2Dt, \quad (1.13)$$

in agreement with Eq. (1.7).

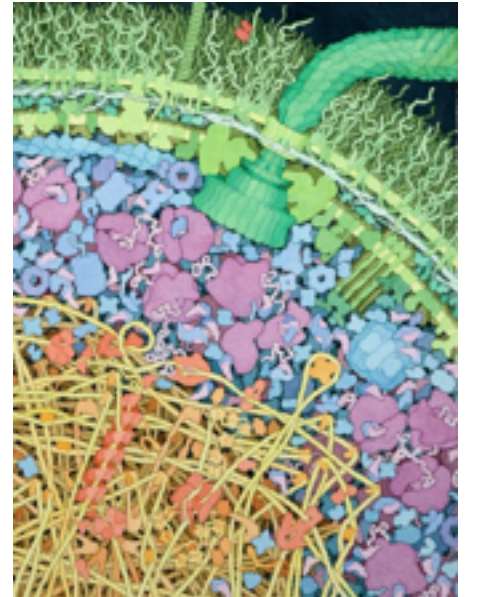
Different types of “diffusion”

Remark One often classifies diffusion processes by the (asymptotic) power-law growth of the mean square displacement,

$$\mathbb{E}[(X(t) - X(0))^2] \sim t^\mu. \quad (1.14)$$

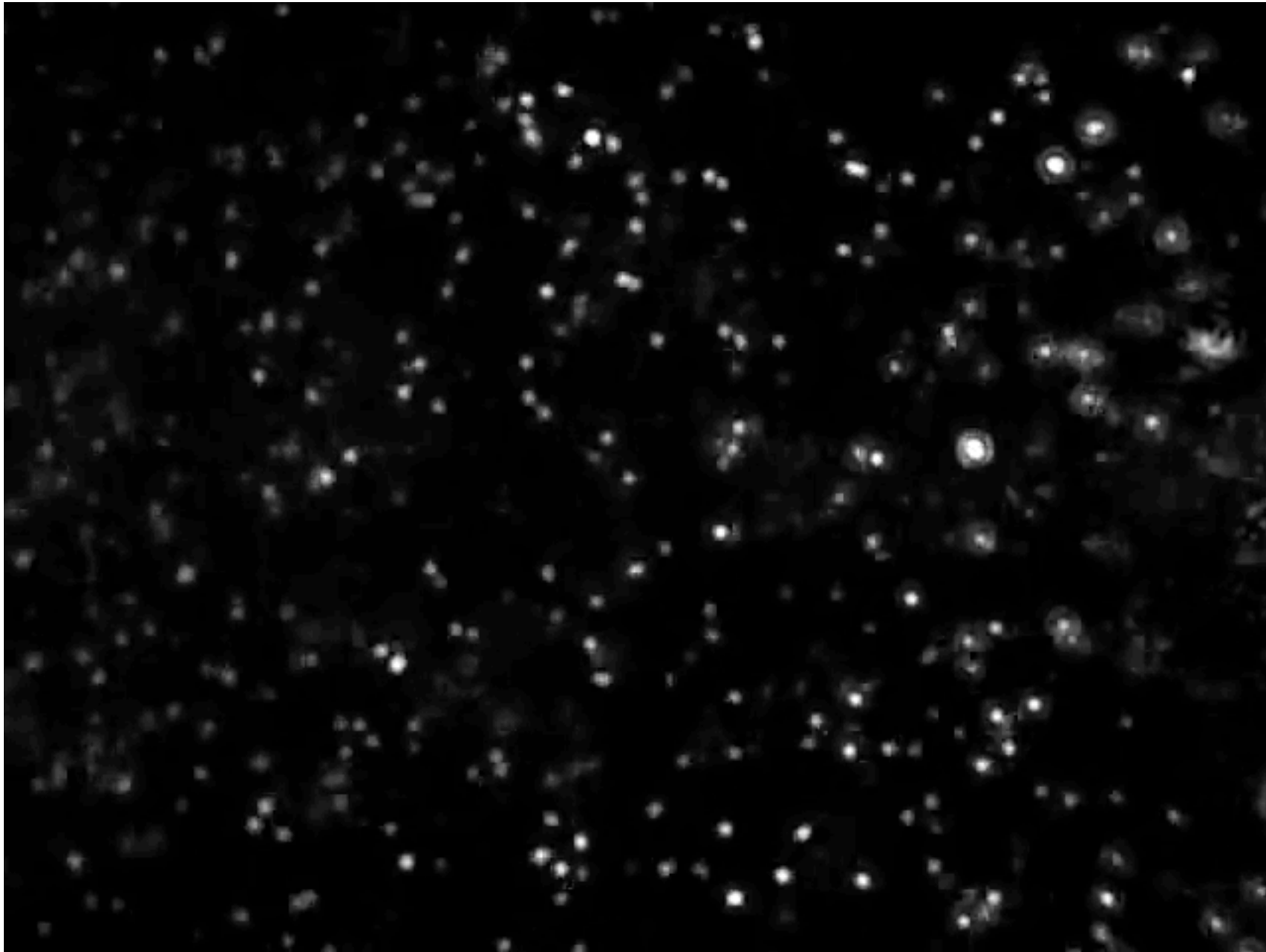
- $\mu = 0$: Static process with no movement.
- $0 < \mu < 1$: Sub-diffusion, arises typically when waiting times between subsequent jumps can be long and/or in the presence of a sufficiently large number of obstacles (e.g. slow diffusion of molecules in crowded cells).
- $\mu = 1$: Normal diffusion, corresponds to the regime governed by the standard Central Limit Theorem (CLT).
- $1 < \mu < 2$: Super-diffusion, occurs when step-lengths are drawn from distributions with infinite variance (Lévy walks; considered as models of bird or insect movements).
- $\mu = 2$: Ballistic propagation (deterministic wave-like process).

Relevance in biology



- **intra**cellular transport
- **inter**cellular transport
- microorganisms must beat BM to achieve directed locomotion
- tracer diffusion = important experimental “tool”
- generalized BMs (polymers, membranes, etc.)

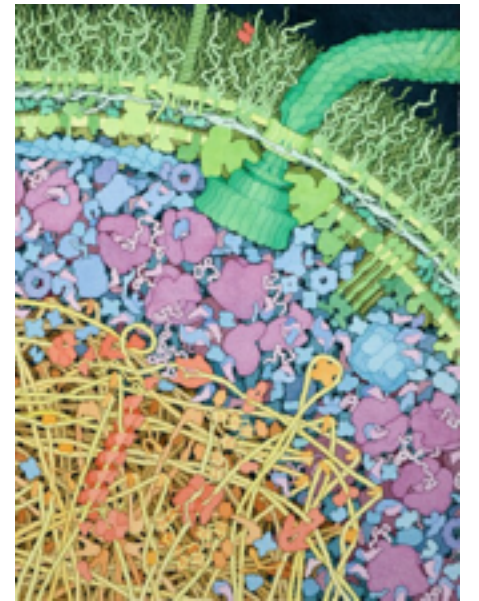
Nano-spheres in water



Rutger Saly

Polymer in a fluid

Dogic lab
(Brandeis)



$< 1\mu m$

Ring-polymer in a fluid

Dogic lab
(Brandeis)



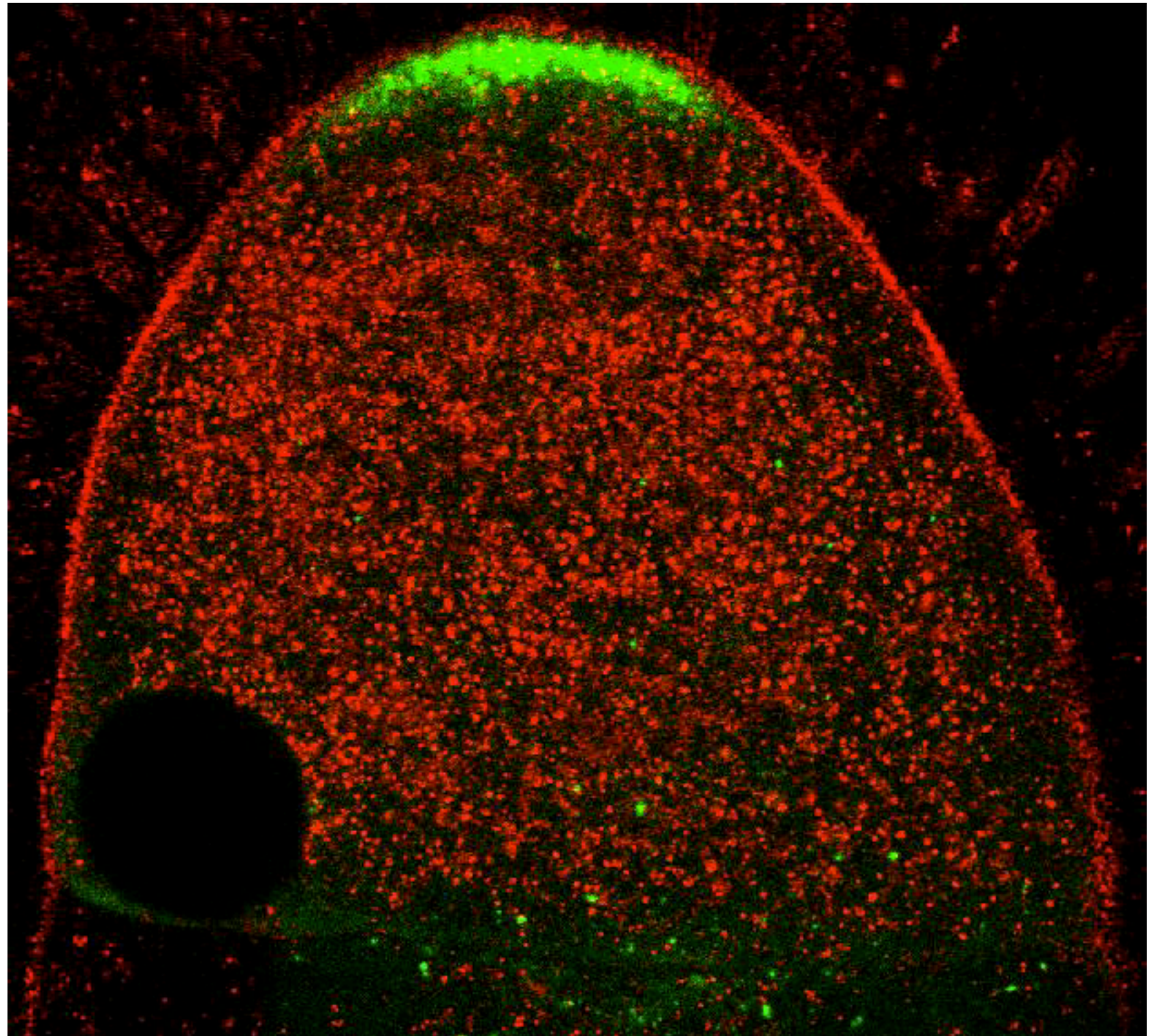
$< 1\mu m$

Flow **in** cells

Flow & transport in cells



Drosophila
embryo

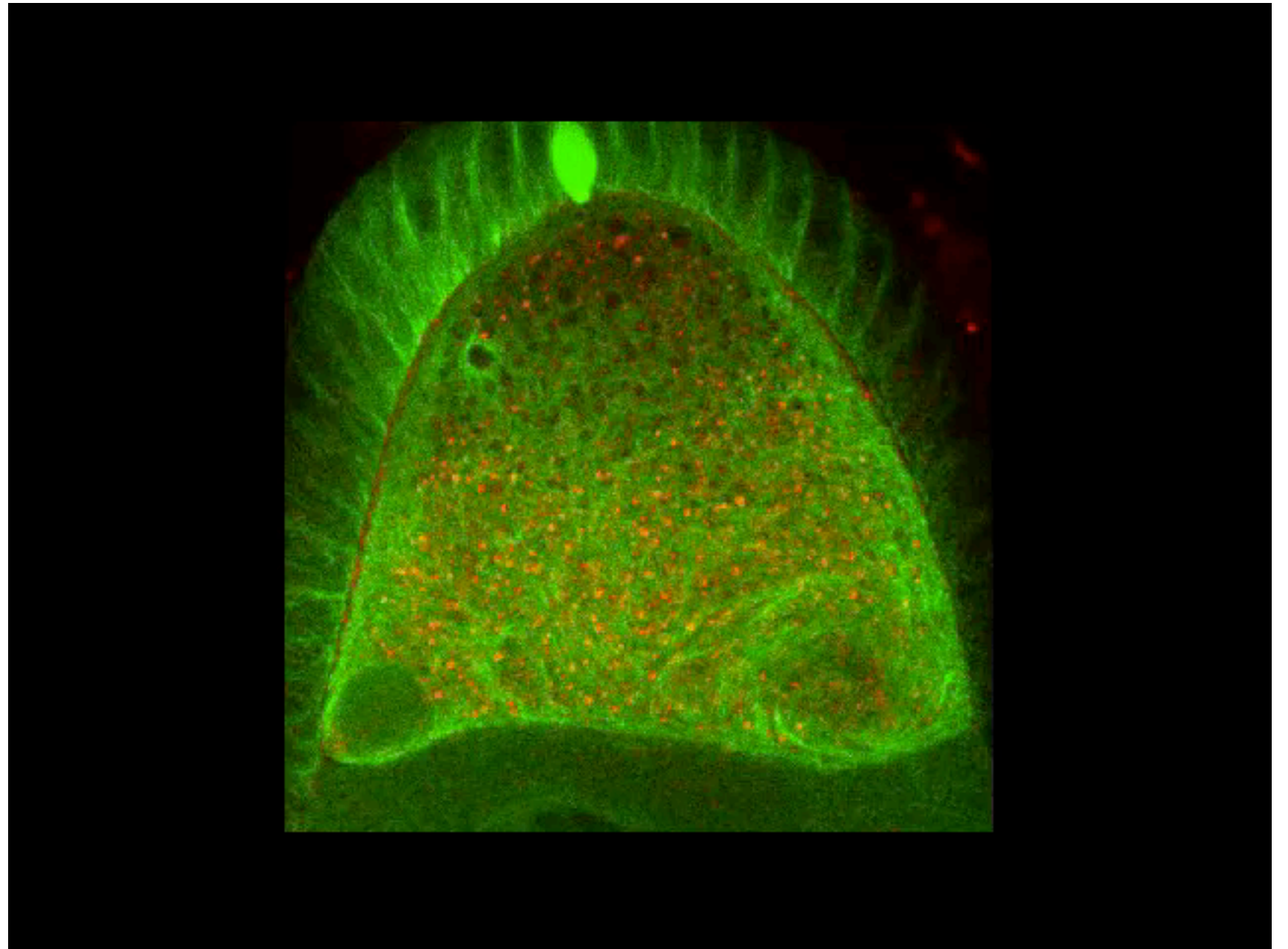


Goldstein lab (Cambridge)

Flow & transport in cells



Drosophila
embryo



Goldstein lab (Cambridge)

Intracellular transport

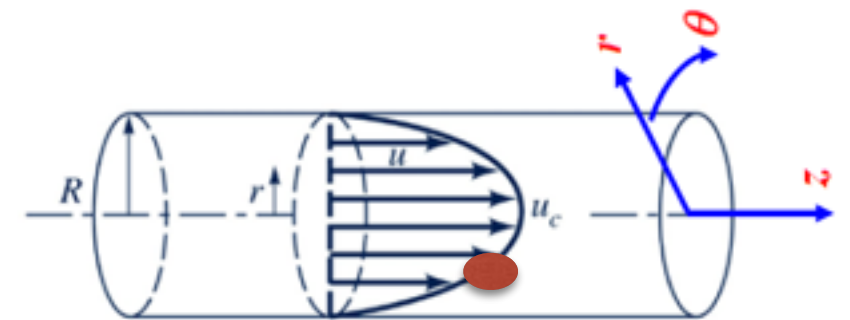
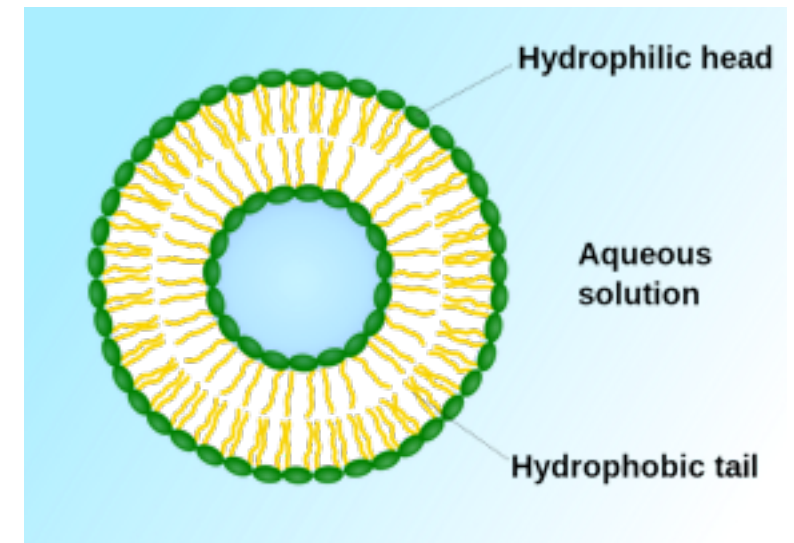
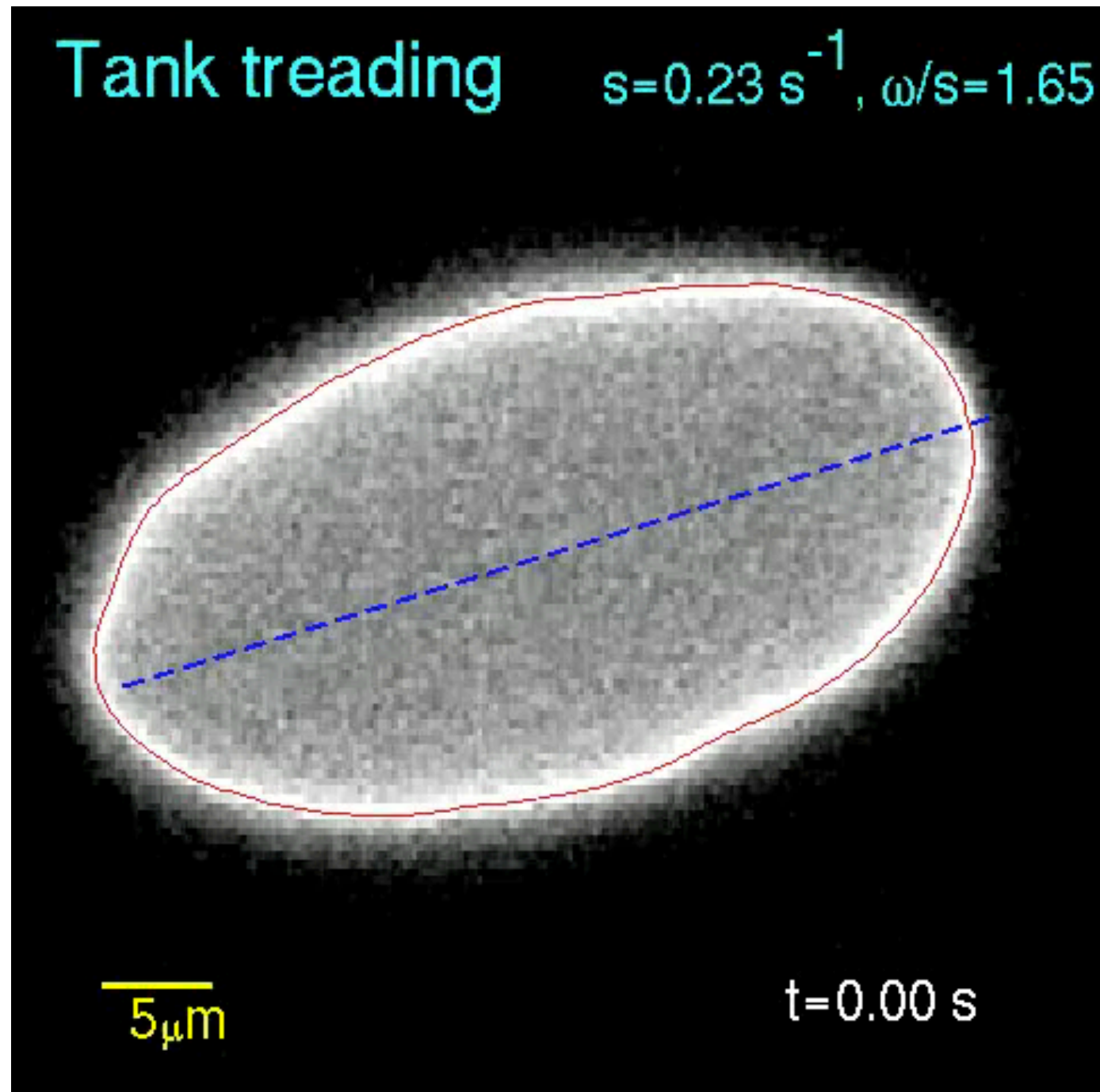


Giant cell

<http://damtp.cam.ac.uk/user/gold/movies.html>

Flow around cells

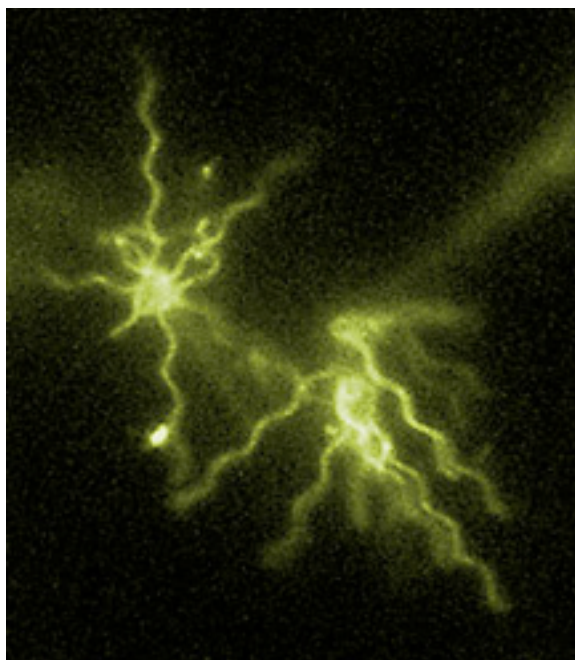
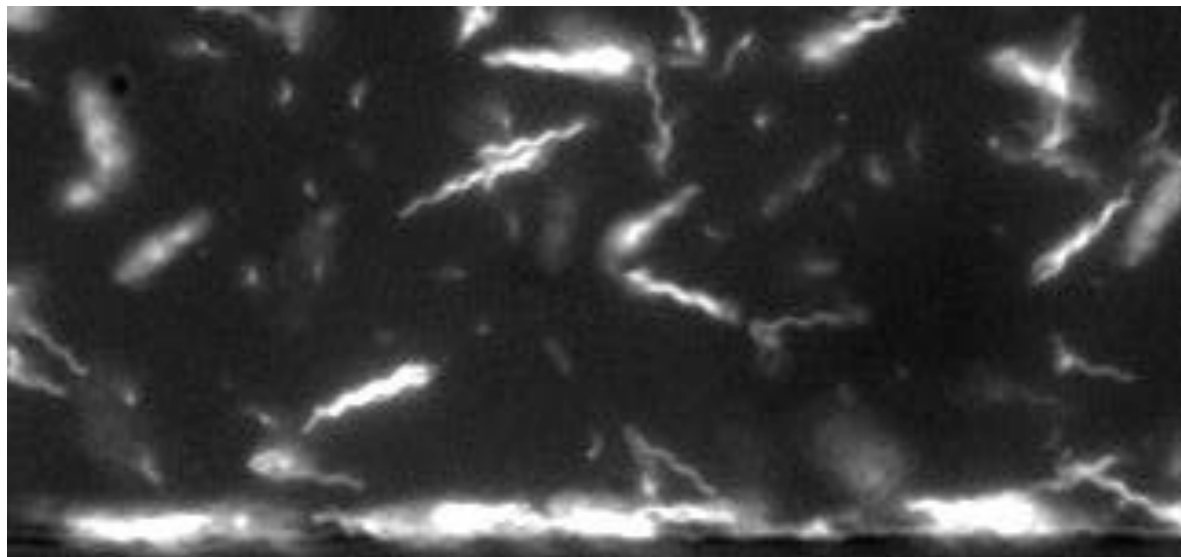
Vesicles in a shear flow



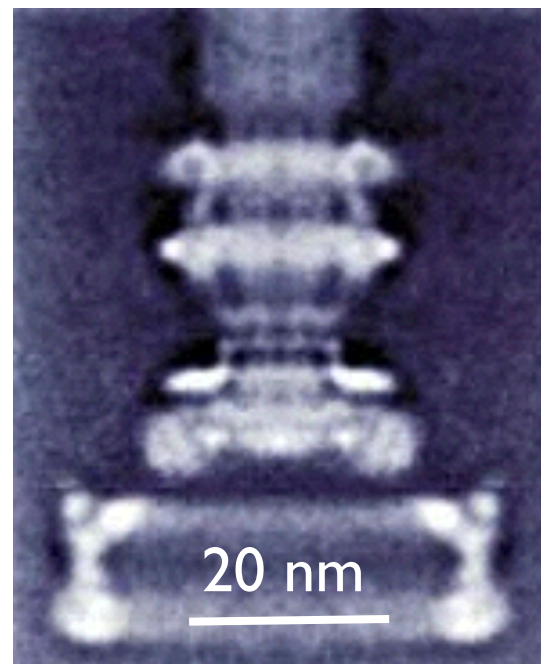
model for
blood cells
dynamics

Swimming bacteria

movie: V. Kantsler

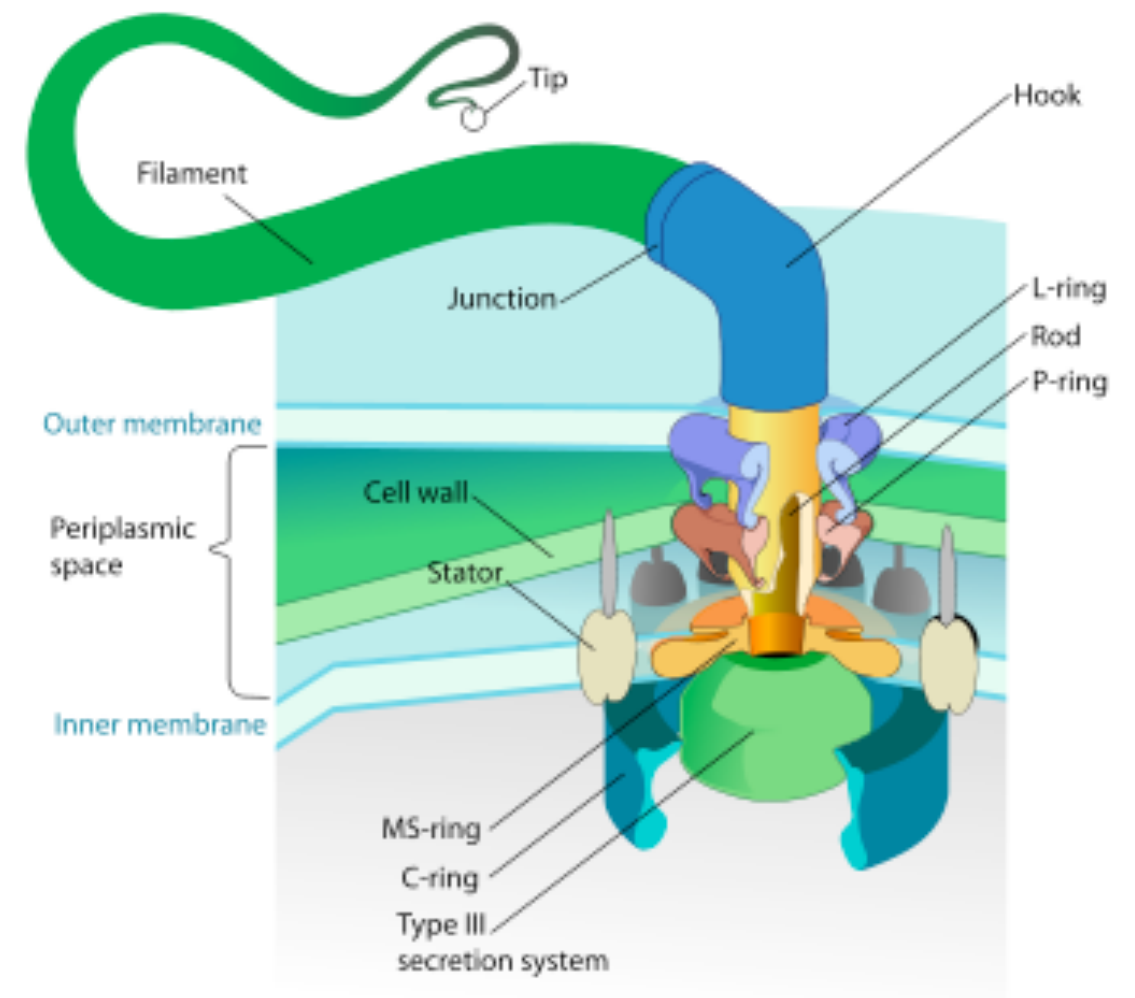


Berg (1999) Physics Today



Chen et al (2011) EMBO Journal

~20 parts



source: wiki

How fast must a cell swim to beat Brownian motion?

$$\langle x^2 \rangle = 2Dt$$

$$D = \frac{kT}{6\pi\eta_0 a}$$

How fast must a cell swim to beat Brownian motion?

$$\langle x^2 \rangle = 2Dt$$

$$D = \frac{kT}{6\pi\eta_0 a}$$

$$kT = 4 \times 10^{-21} \text{ J}$$

$$a \sim 1 \mu m$$

$$\gamma_S = 6\pi\eta a \sim 2 \times 10^{-8} \text{ kg/s}$$

How fast must a cell swim to beat Brownian motion?

$$\langle x^2 \rangle = 2Dt$$

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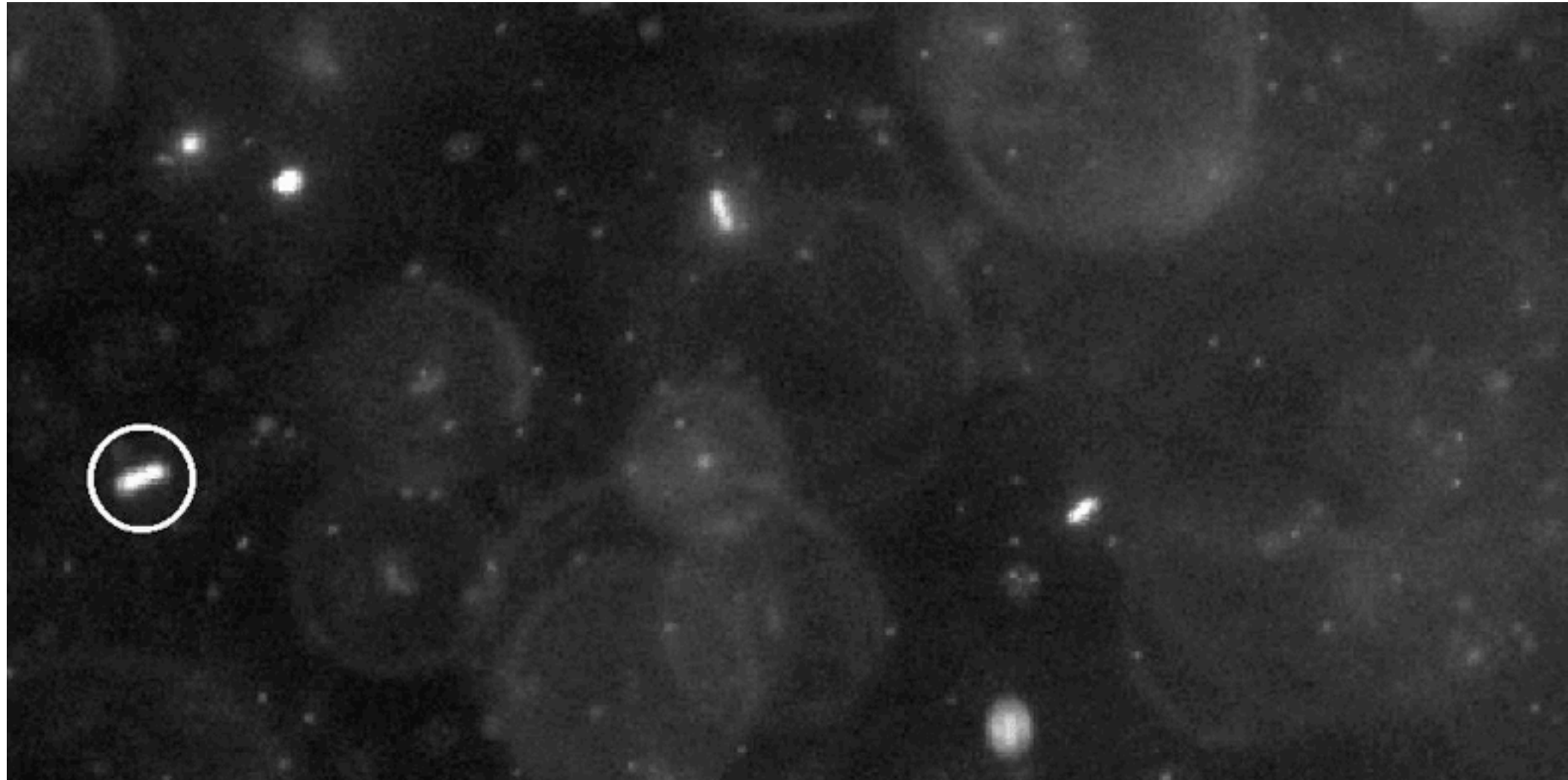
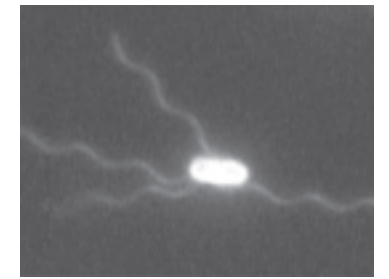
$$\gamma_S = 6\pi\eta a \sim 2 \times 10^{-8} \text{ kg/s}$$

Hence, we find for the diffusion constant

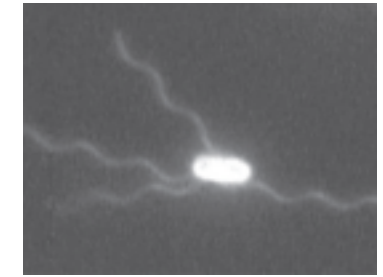
$$D \sim 0.2 \mu\text{m}^2/\text{s}$$

Assuming a run length ~ 1 s, Brownian motion would move a micron-sized bacterium by approximately $0.5 \mu\text{m}$ per second. Thus a bacterium should swim at last $5\text{-}10 \mu\text{m/s}$, which is close to typical swim bacterial speeds.

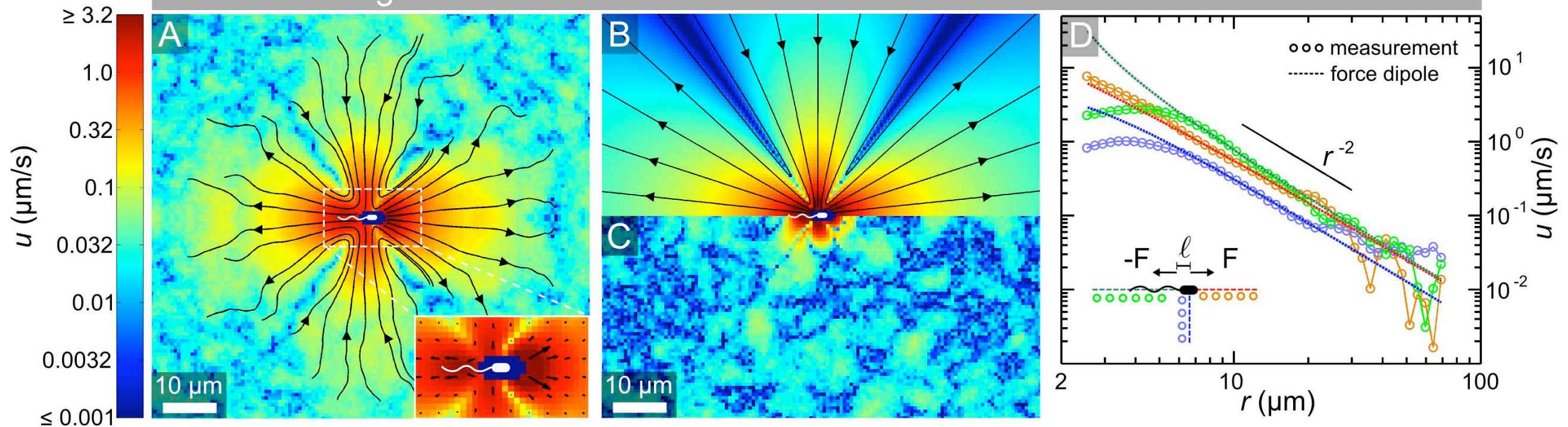
E.coli (non-tumbling HCB 437)



E.coli (non-tumbling HCB 437)



Free swimming



$$\mathbf{u}(\mathbf{r}) = \frac{A}{|\mathbf{r}|^2} \left[3(\hat{\mathbf{r}} \cdot \hat{\mathbf{d}})^2 - 1 \right] \hat{\mathbf{r}}, \quad A = \frac{\ell F}{8\pi\eta}, \quad \hat{\mathbf{r}} = \frac{\mathbf{r}}{|\mathbf{r}|}$$

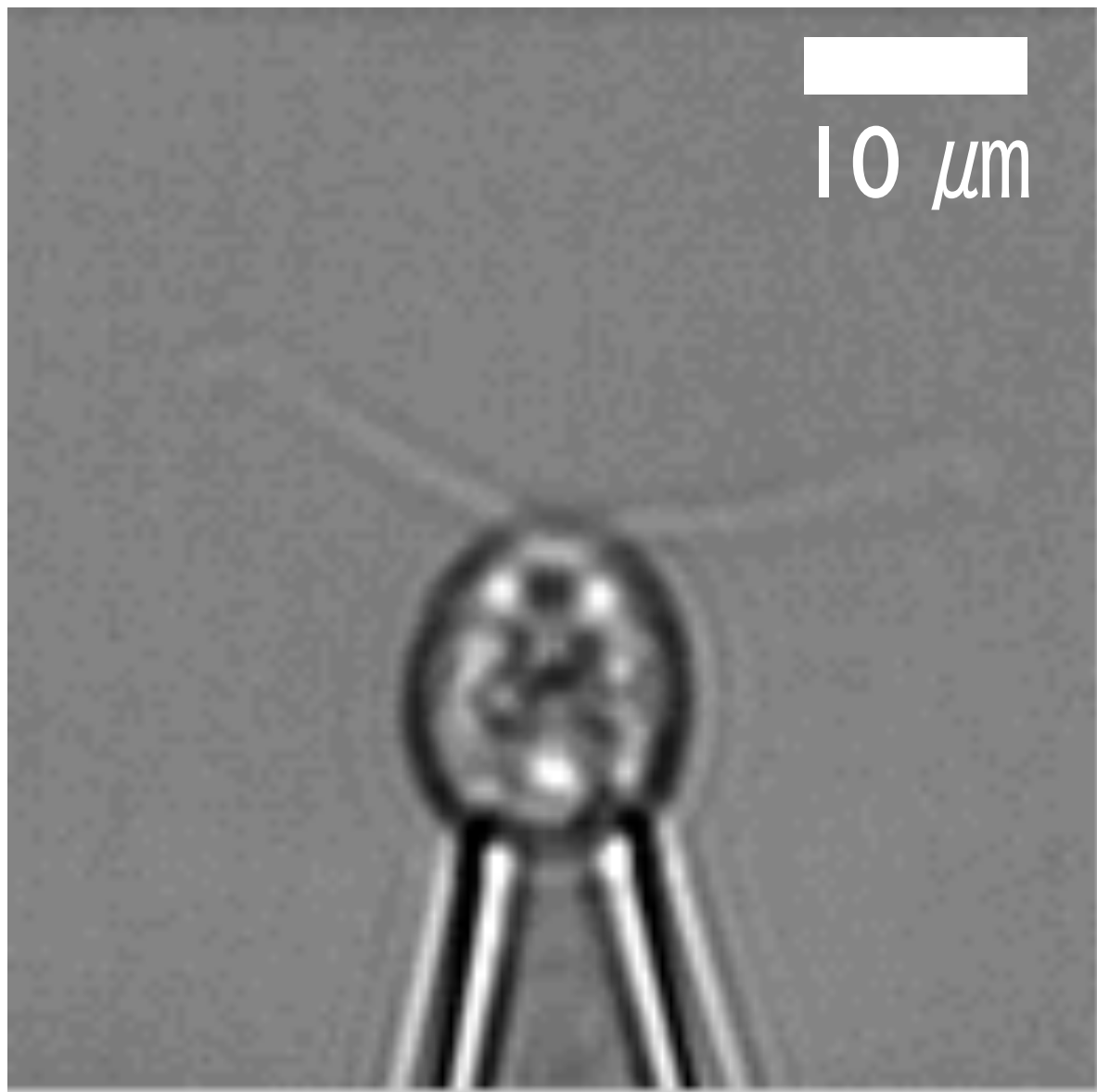
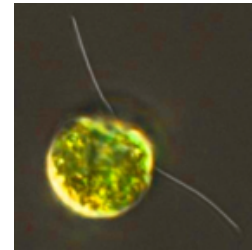
$$V_0 = 22 \pm 5 \text{ } \mu\text{m/s}$$

$$\ell = 1.9 \text{ } \mu\text{m}$$

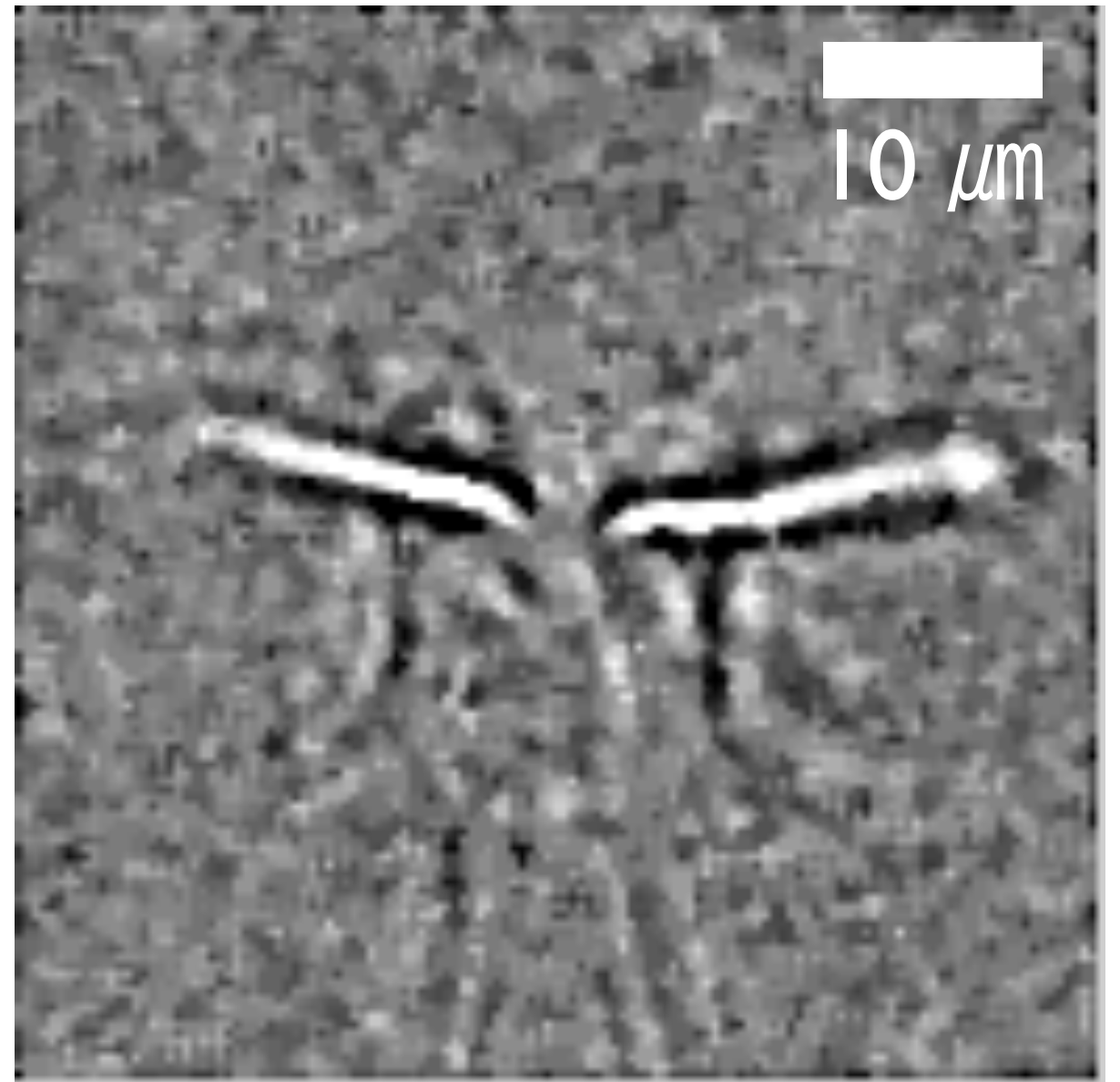
$$F = 0.42 \text{ pN}$$

weak 'pusher' dipole

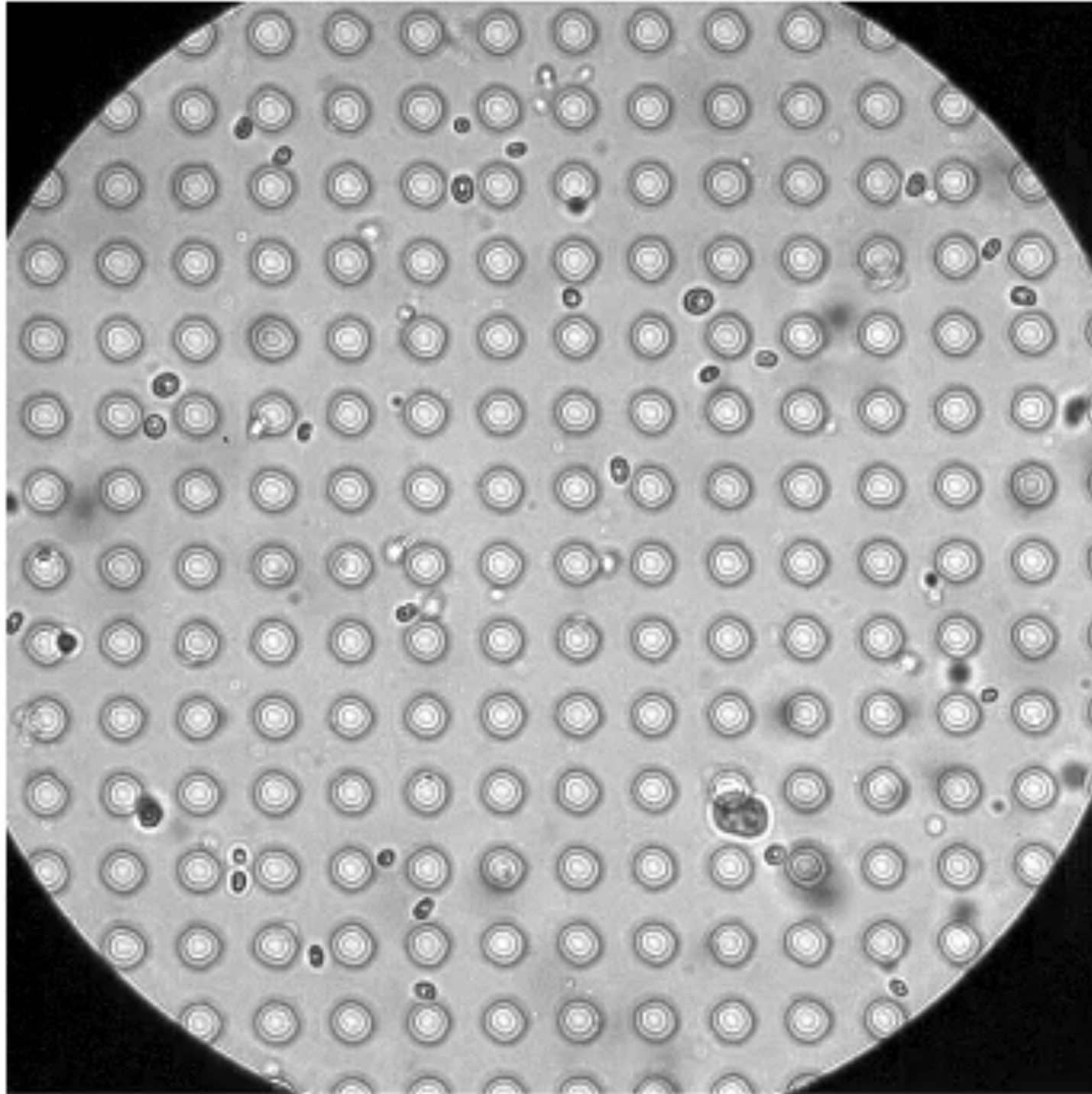
Chlamydomonas alga



~ 50 beats / sec

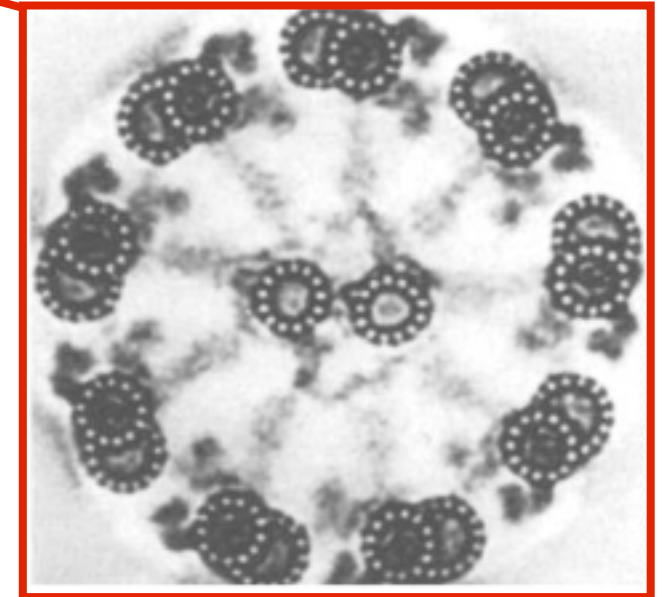
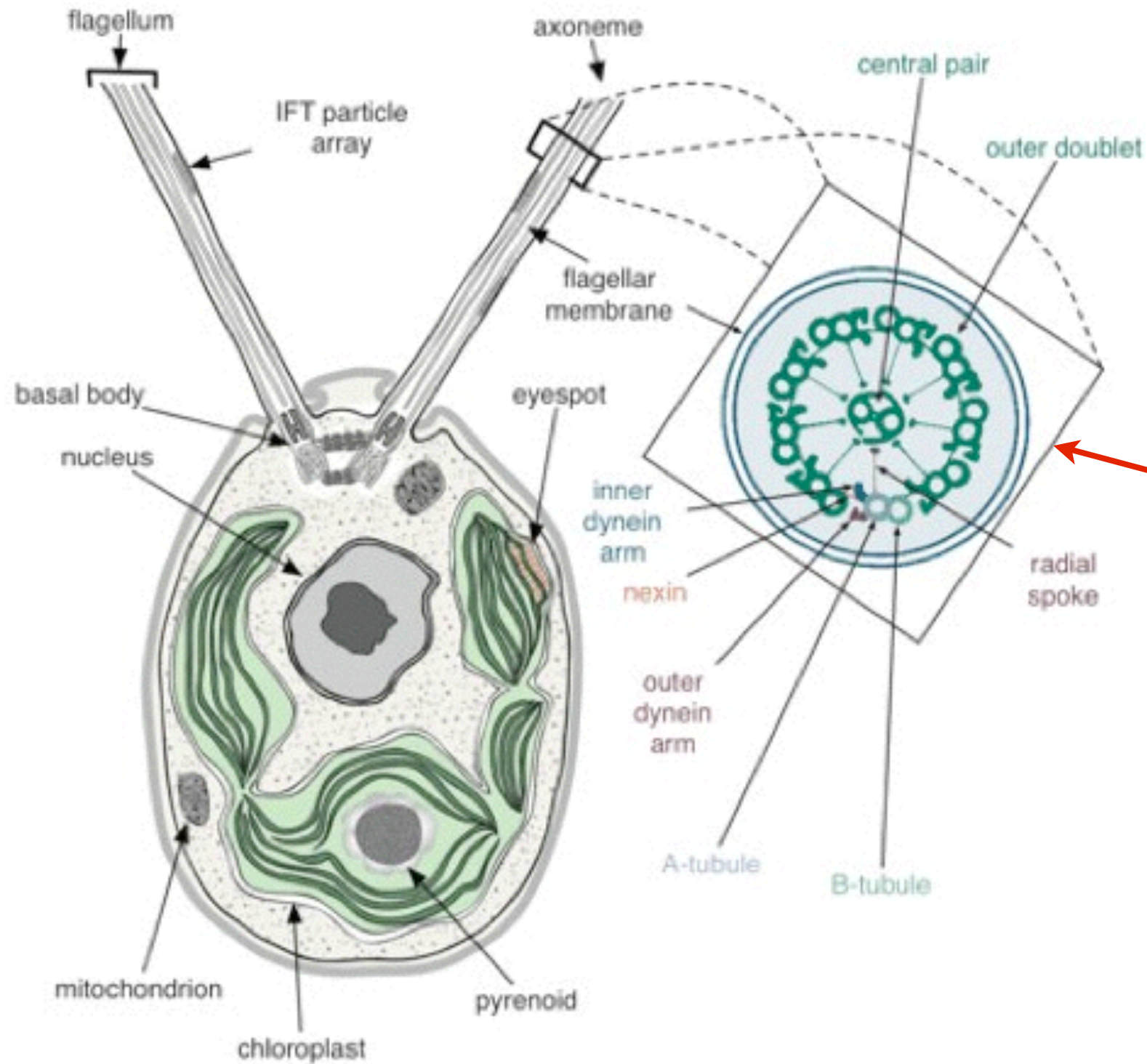
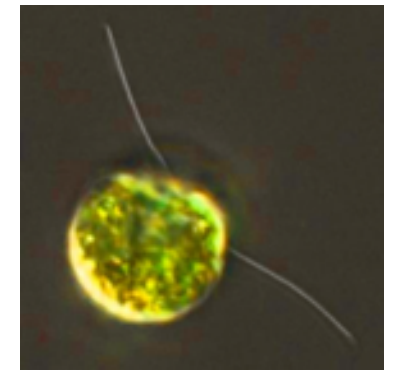


speed ~100 $\mu\text{m/s}$

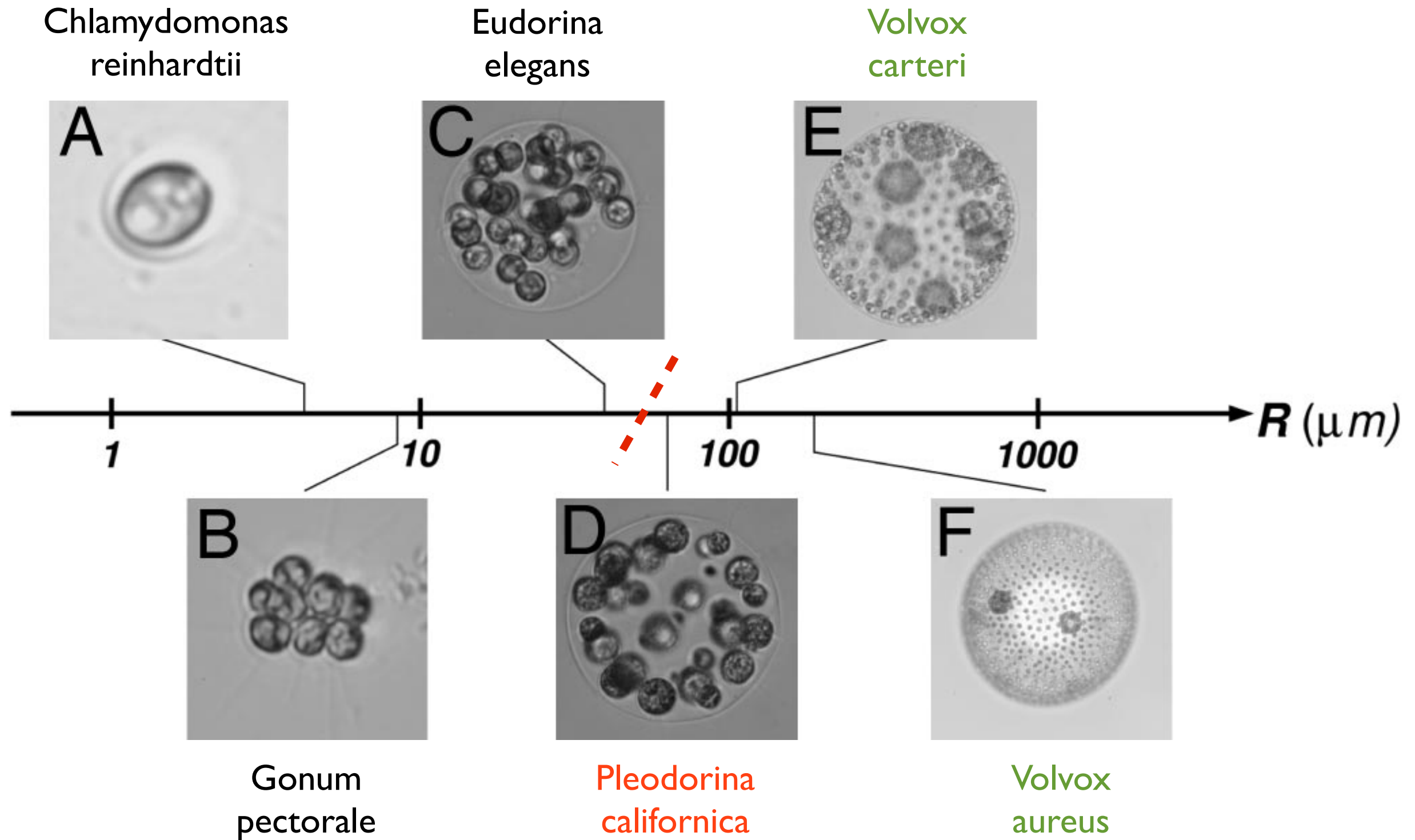


Video: Vasily Kantsler

Chlamydomonas



Evolution of multicellularity

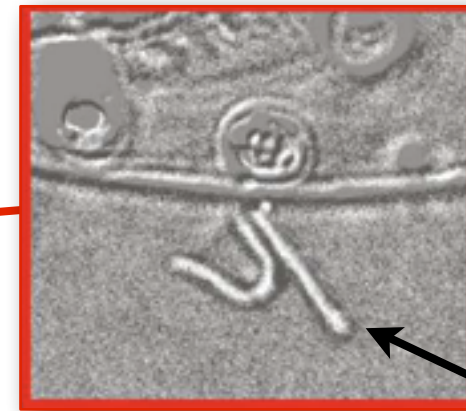
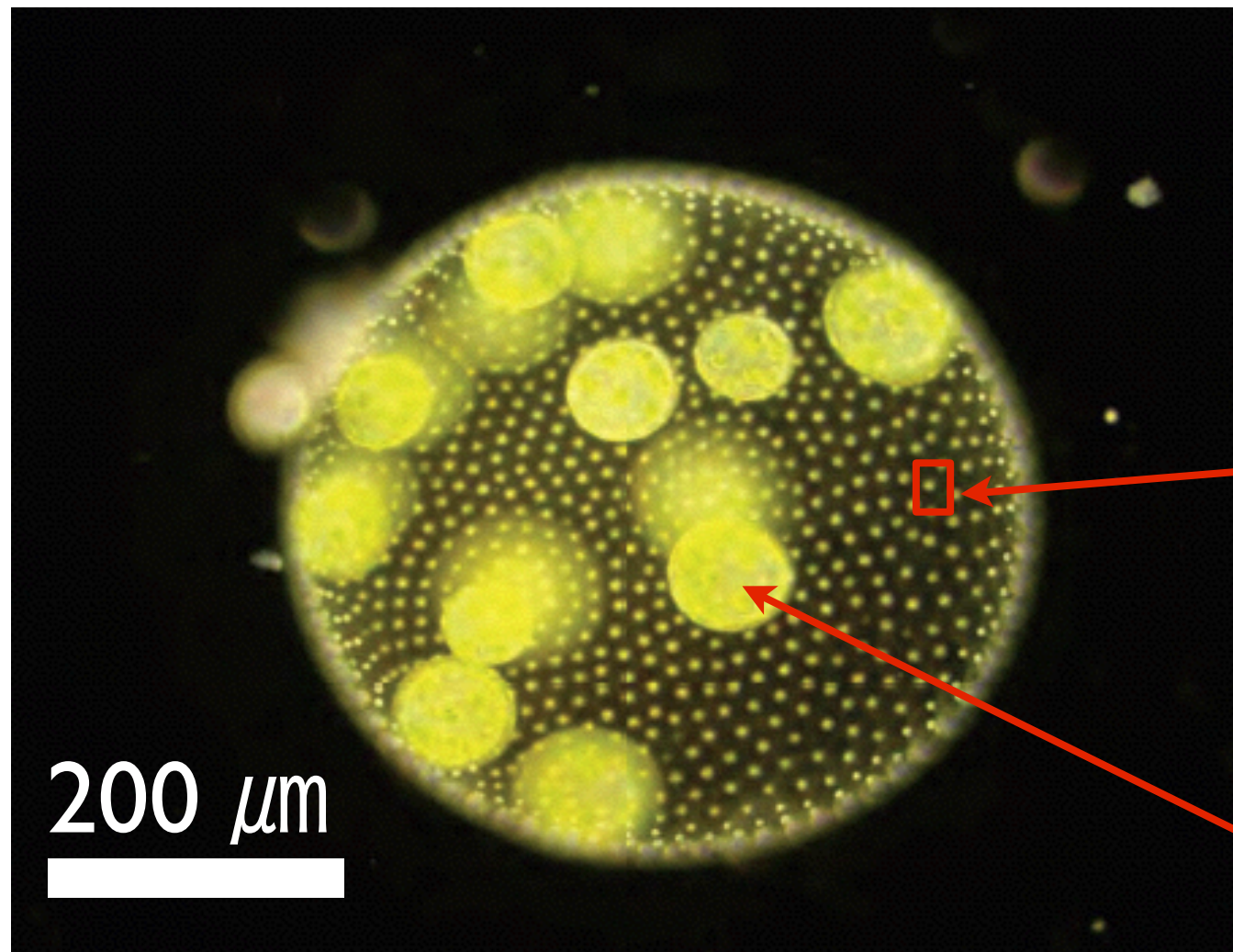


Volvox carteri

somatic
cell

cilia

daughter colony



Asexual reproduction & inversion

Time lapse movie showing multiple
embryonic inversions

Videos show 3D renderings of images acquired using
Selective Plane Illumination Microscopy (SPIM)
and chlorophyll autofluorescence

scale bar: 100 microns

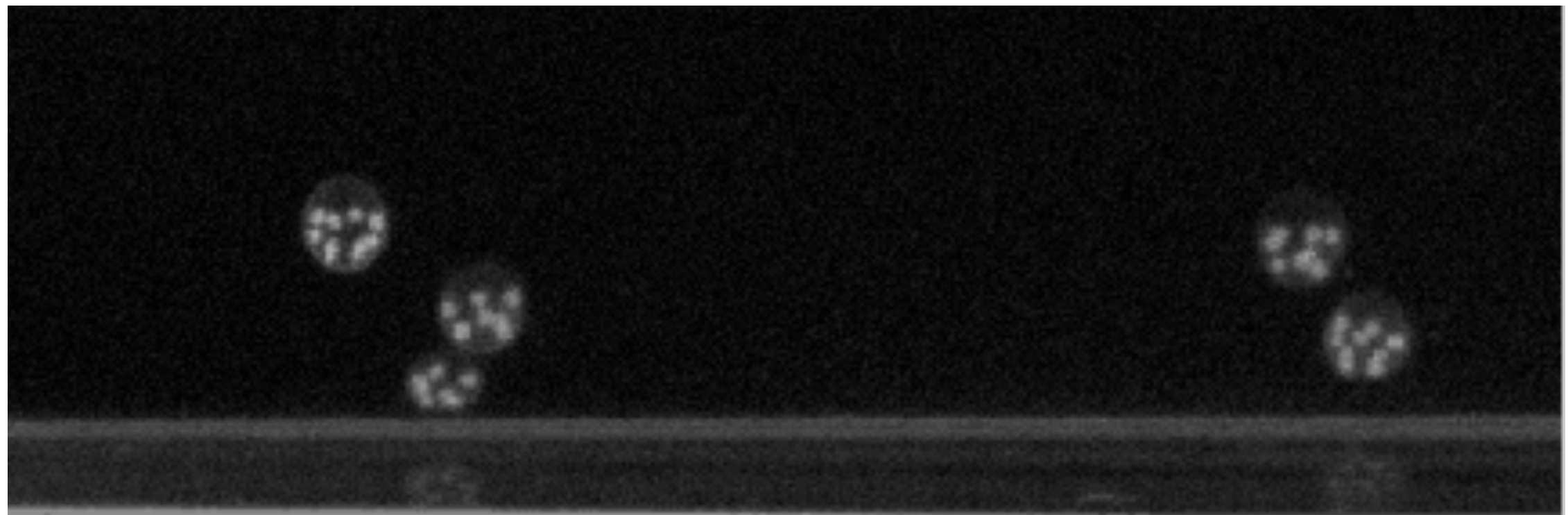
Volvox carteri

somatic
cell

cilia

daughter colony

200 μm



Volvox

Meta-chronal waves

Brumley et al (2012) PRL

Ecological implications & technical applications

Sedimentation

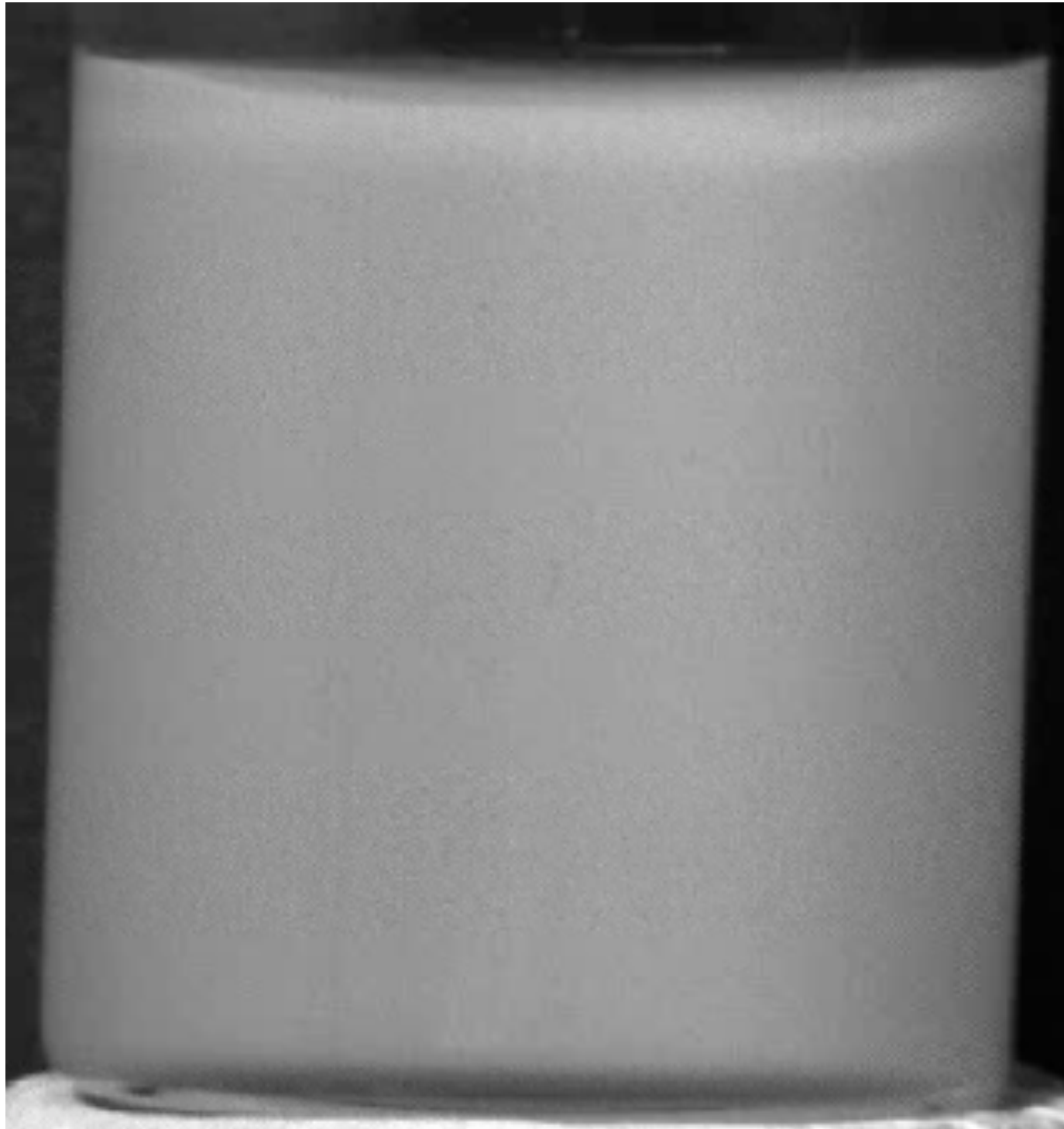


Mississippi

NASA Earth Observatory



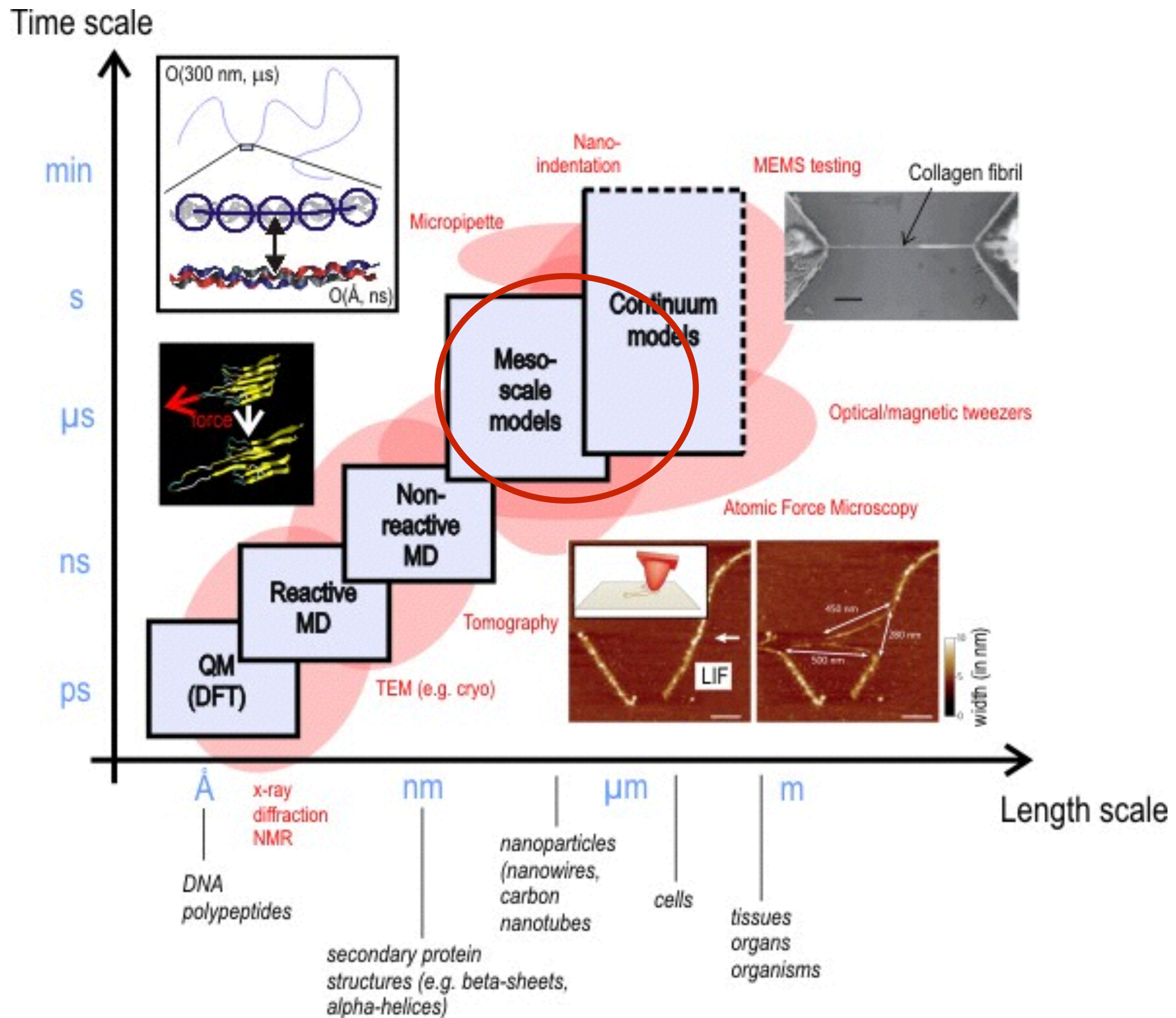
Sedimentation

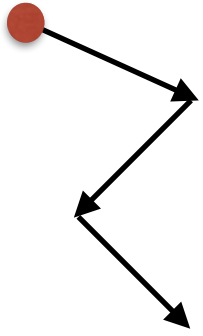


Particle
separation

Brownian motion of small objects in fluids
is biologically and technologically relevant
(and interesting)

How can we describe these phenomena
mathematically ?

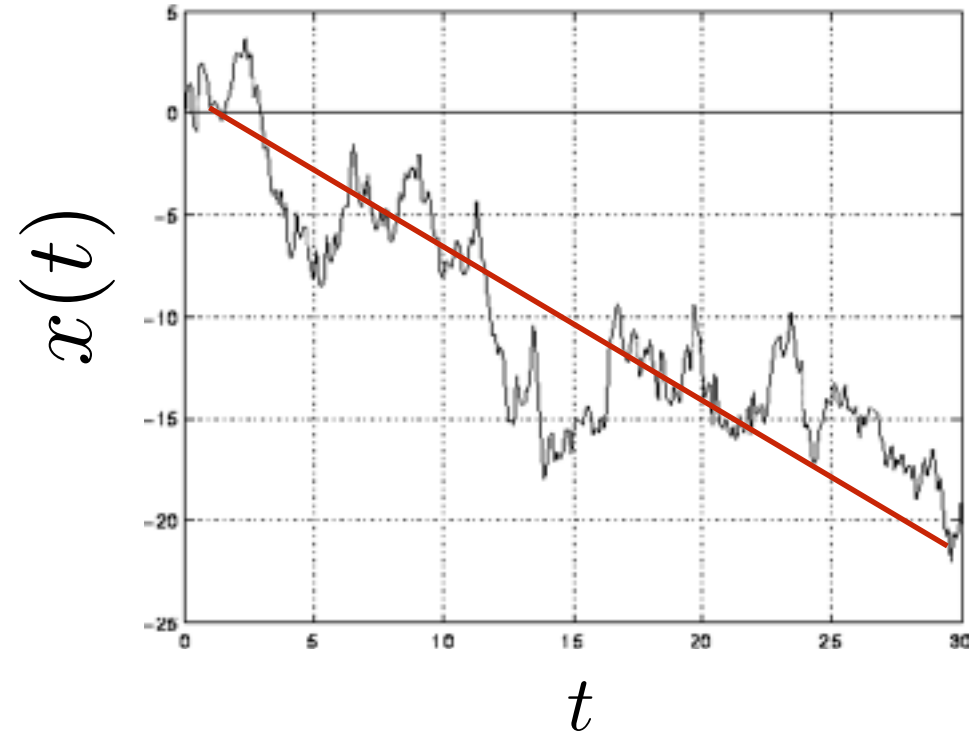




Basic idea

Split dynamics into

- deterministic part (**drift**)
- random part (**diffusion**, “noise”)



$$\dot{x}(t) = f(x(t)) + \sqrt{2D} \xi(t)$$

Stochastic **D**ifferential **E**quation



Over-damped dynamics

Newton: $m\ddot{x}(t) = F(x(t)) + S(\dot{x}(t)) + L(t)$

Stokes: $m\ddot{x}(t) = F(x(t)) - \gamma\dot{x}(t) + L(t)$

Neglect inertia ($Re=0$): $m\ddot{x}(t) \rightarrow 0$

$$0 = F(x(t)) - \gamma\dot{x}(t) + L(t)$$

$$\dot{x}(t) = f(x(t)) + \sqrt{2D} \xi(t)$$



Langevin equation

$$\dot{x}(t) = f(x(t)) + \sqrt{2D} \xi(t)$$



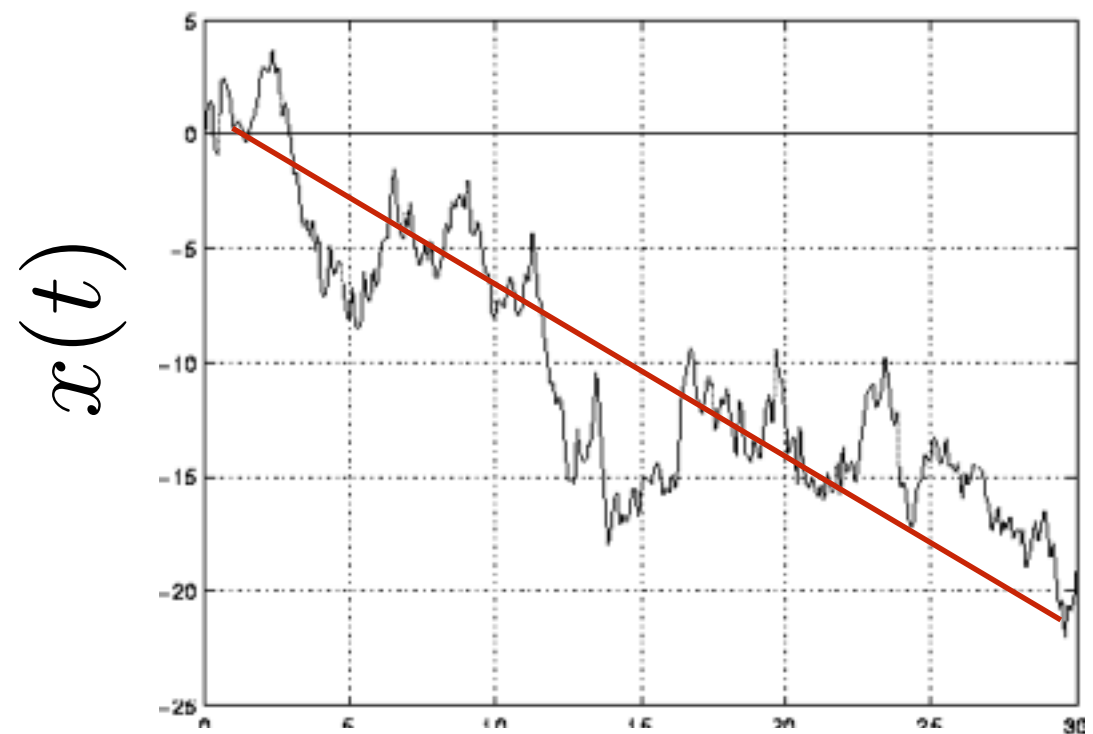
How can we characterize randomness?

Continuous representation of Brownian trajectories ?

1.2 Brownian motion (constant drift)

$$\dot{X}(t) = u + \sqrt{2D} \xi(t)$$

$$dB(t) = \xi(t) dt$$



$$dX(t) = u dt + \sqrt{2D} dB(t)$$

SDE

$B(t)$: Wiener process



Wiener process

$$dX(t) = u dt + \sqrt{2D} dB(t). \quad (1.25)$$

Here, $dX(t) = X(t + dt) - X(t)$ is increment of the stochastic particle trajectory $X(t)$, whilst $dB(t) = B(t + dt) - B(t)$ denotes an increment of the standard Brownian motion (or Wiener) process $B(t)$, uniquely defined by the following properties³:

- (i) $B(0) = 0$ with probability 1.
- (ii) $B(t)$ is stationary, i.e., for $t > s \geq 0$ the increment $B(t) - B(s)$ has the same distribution as $B(t - s)$.
- (iii) $B(t)$ has independent increments. That is, for all $t_n > t_{n-1} > \dots > t_2 > t_1$, the random variables $B(t_n) - B(t_{n-1}), \dots, B(t_2) - B(t_1), B(t_1)$ are independently distributed (i.e., their joint distribution factorizes).
- (iv) $B(t)$ has Gaussian distribution with variance t for all $t \in (0, \infty)$.
- (v) $B(t)$ is continuous with probability 1.

The probability distribution \mathbb{P} governing the driving process $B(t)$ is commonly known as the Wiener measure.



Langevin equation

$$dX(t) = u dt + \sqrt{2D} dB(t). \quad (1.25)$$

Although the derivative $\xi(t) = dB/dt$ is not well-defined mathematically, Eq. (1.25) is in the physics literature often written in the form

$$\dot{X}(t) = u + \sqrt{2D} \xi(t). \quad (1.26)$$

The random driving function $\xi(t)$ is then referred to as Gaussian white noise, characterized by

$$\langle \xi(t) \rangle = 0, \quad \langle \xi(t) \xi(s) \rangle = \delta(t - s), \quad (1.27)$$

with $\langle \cdot \rangle$ denoting an average with respect to the Wiener measure.

$$\delta(x) = \begin{cases} +\infty, & x = 0 \\ 0, & \text{otherwise} \end{cases} \quad f(y) = \int_{-\infty}^{+\infty} dx \, \delta(x - y) f(x)$$

Dirac's Delta-function

Mean displacement

$$\dot{X}(t) = \sqrt{2D} \xi(s)$$

Direct integration with $X(0) = 0$

$$X(t) = \sqrt{2D} \int_0^t ds \xi(s)$$

Averaging

$$\langle X(t) \rangle = \left\langle \sqrt{2D} \int_0^t ds \xi(s) \right\rangle = \sqrt{2D} \int_0^t ds \langle \xi(s) \rangle = 0$$

$$\langle \xi(t) \rangle = 0$$

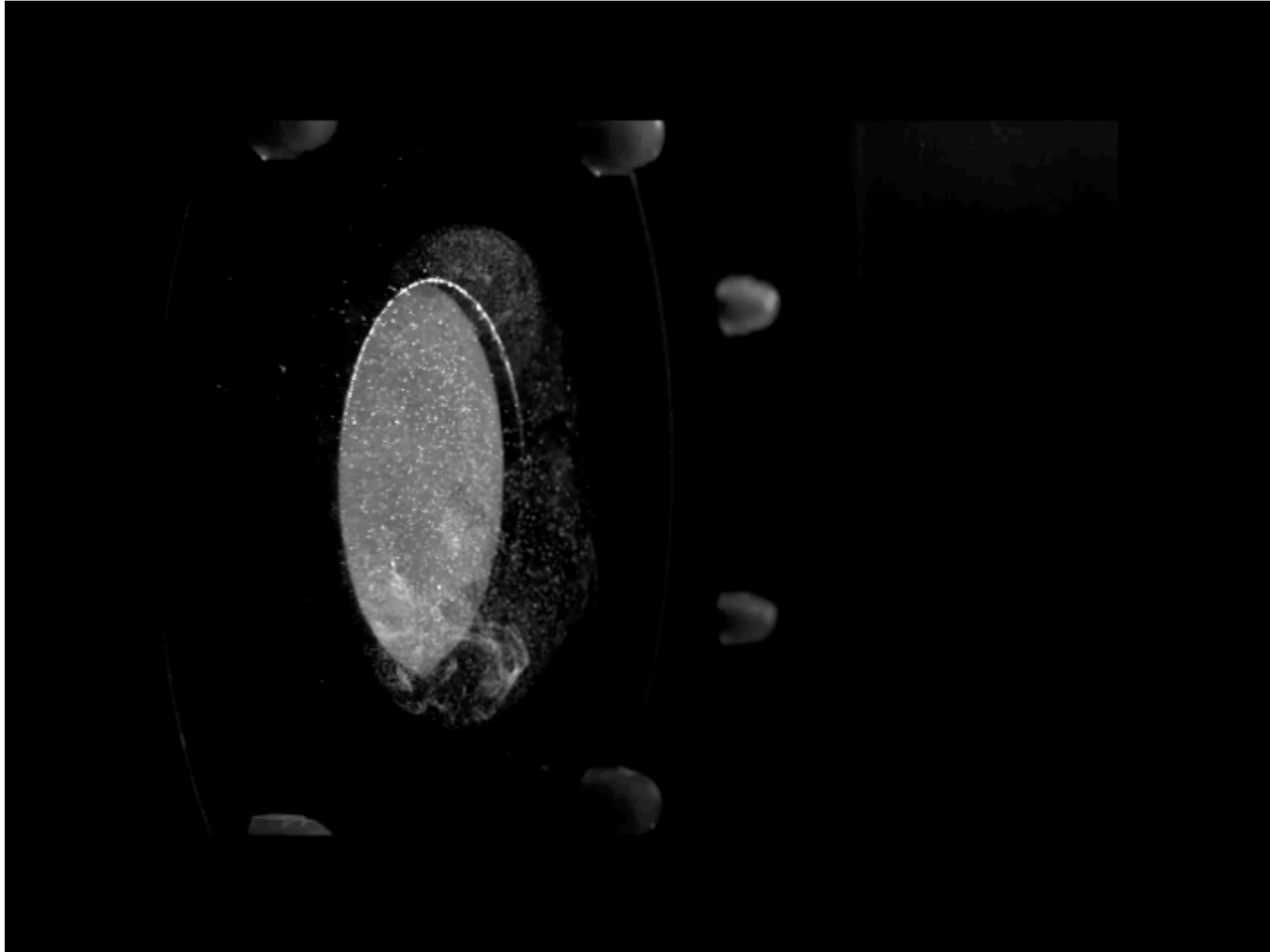


Mean square displacement

$$X(t) = \sqrt{2D} \int_0^t ds \xi(s)$$

$$\begin{aligned} \langle X(t)^2 \rangle &= \left\langle \left[\sqrt{2D} \int_0^t ds \xi(s) \right] \cdot \left[\sqrt{2D} \int_0^t du \xi(u) \right] \right\rangle \\ &= \left\langle 2D \int_0^t ds \int_0^t du \xi(s) \cdot \xi(u) \right\rangle \\ &= 2D \int_0^t ds \int_0^t du \langle \xi(s) \cdot \xi(u) \rangle \\ &= 2D \int_0^t ds \int_0^t du \delta(s - u) \\ &= 2D \int_0^t ds \\ &= 2Dt \end{aligned}$$

Knotted water



Irvine lab (Chicago)