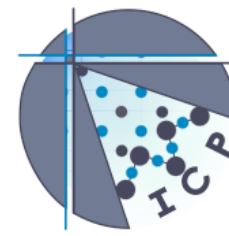


University of Stuttgart
Germany

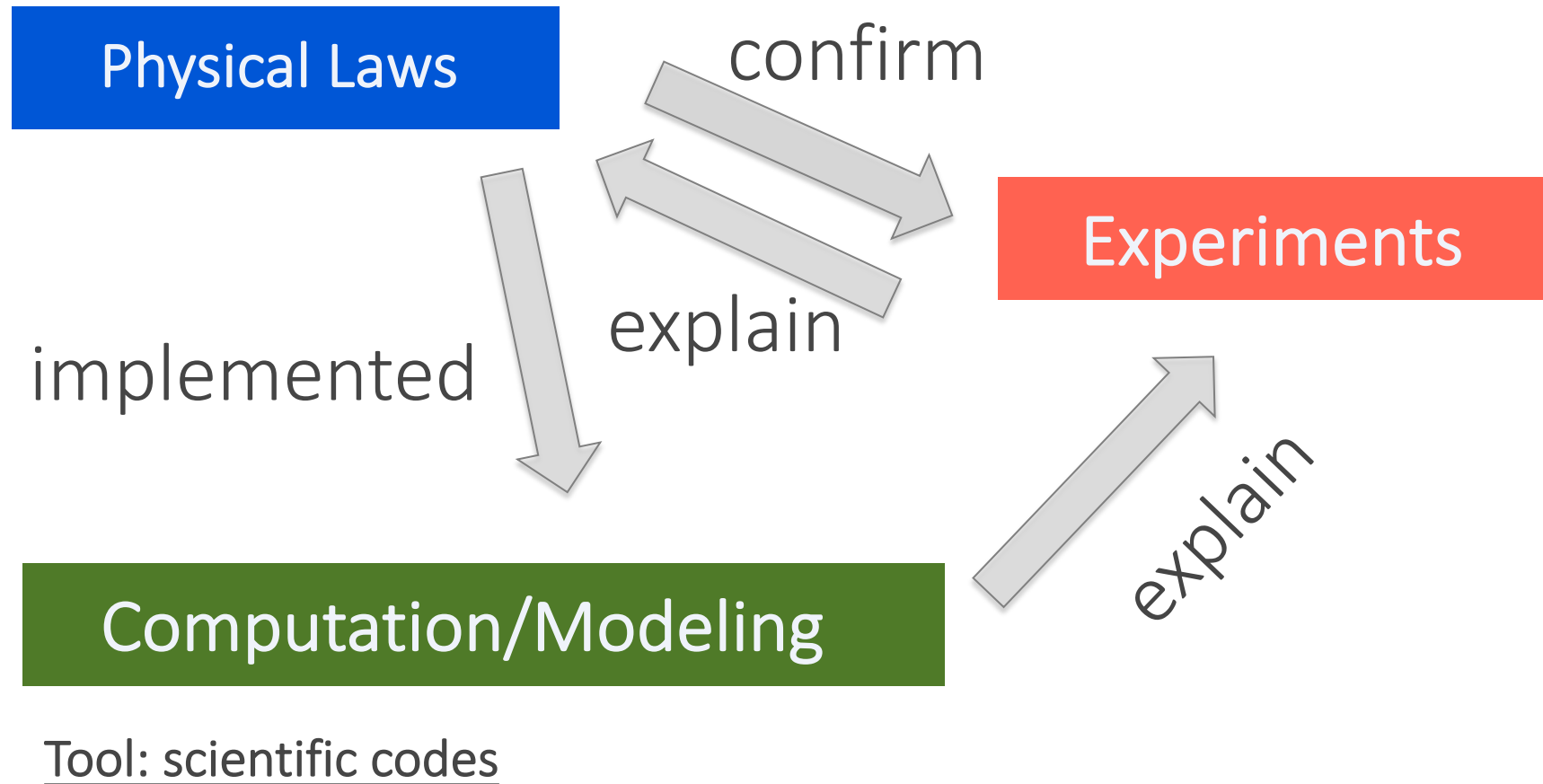


INSTITUTE FOR
COMPUTATIONAL
PHYSICS

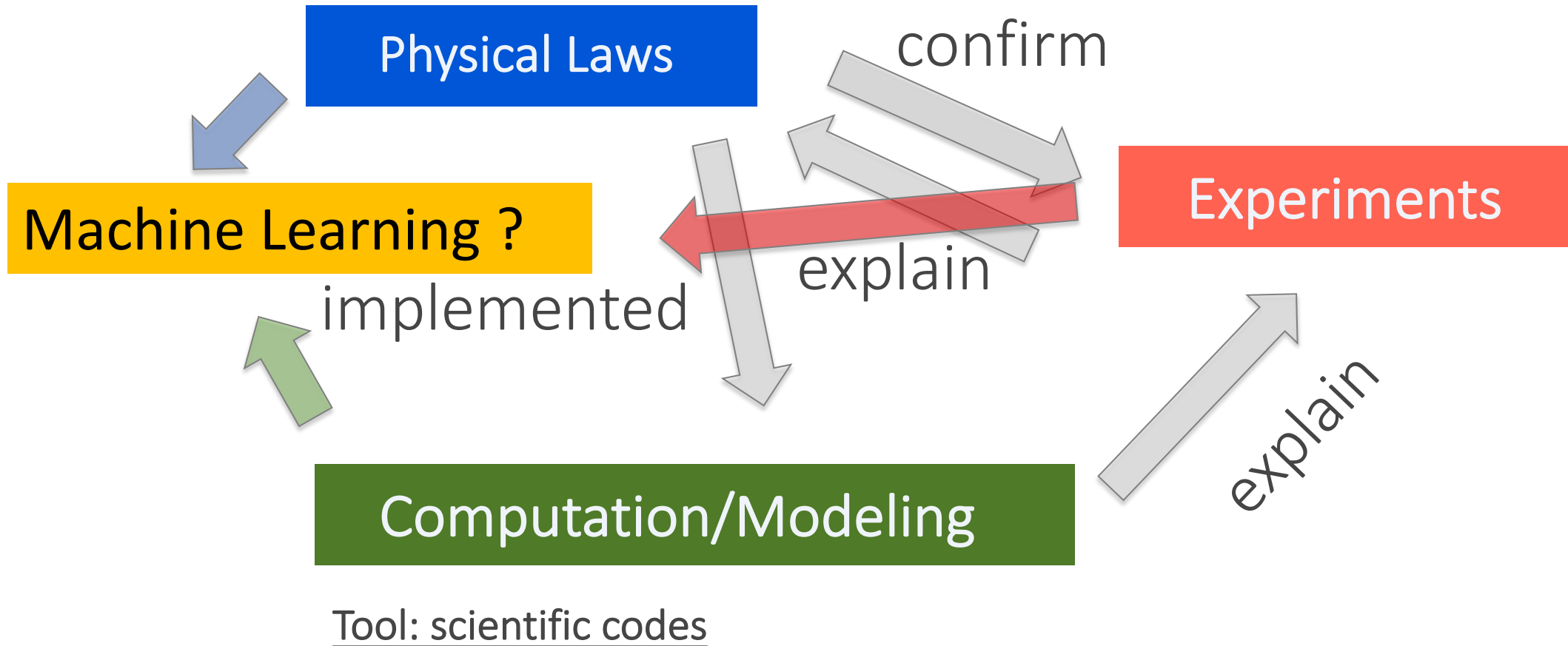
Research at the Institute for Computational Physics

Christian Holm, Rudolf Weeber, Slavko Kondrat
Institut für Computerphysik, Universität Stuttgart, Allmandring 3
Stuttgart, Germany

The Way Physics works today...



The Way Physics works tomorrow...??



Institut for Computational Physics (ICP)

C. Holm (Director)

Theory and Simulations of Soft
charged and dipolar matter
Machine Learning for Soft Matter

R. Weeber (permanent staff)

Magnetic Soft Matter, ESPResSo
Software Suite

**S. Kondrat (part time here
permanent in Academy of
Sciences, Warsaw):**

Soft Matter Theory,
Supercapacitor applications

**S. Tovey (part time here
Senior scientist at Quantum
Brilliance):**

ML in Physics

- Perform frontier research through high level publications
- Develop scientific computational tools and algorithms
- Education and teaching in theoretical and computational physics

Soft Matter Physics.....

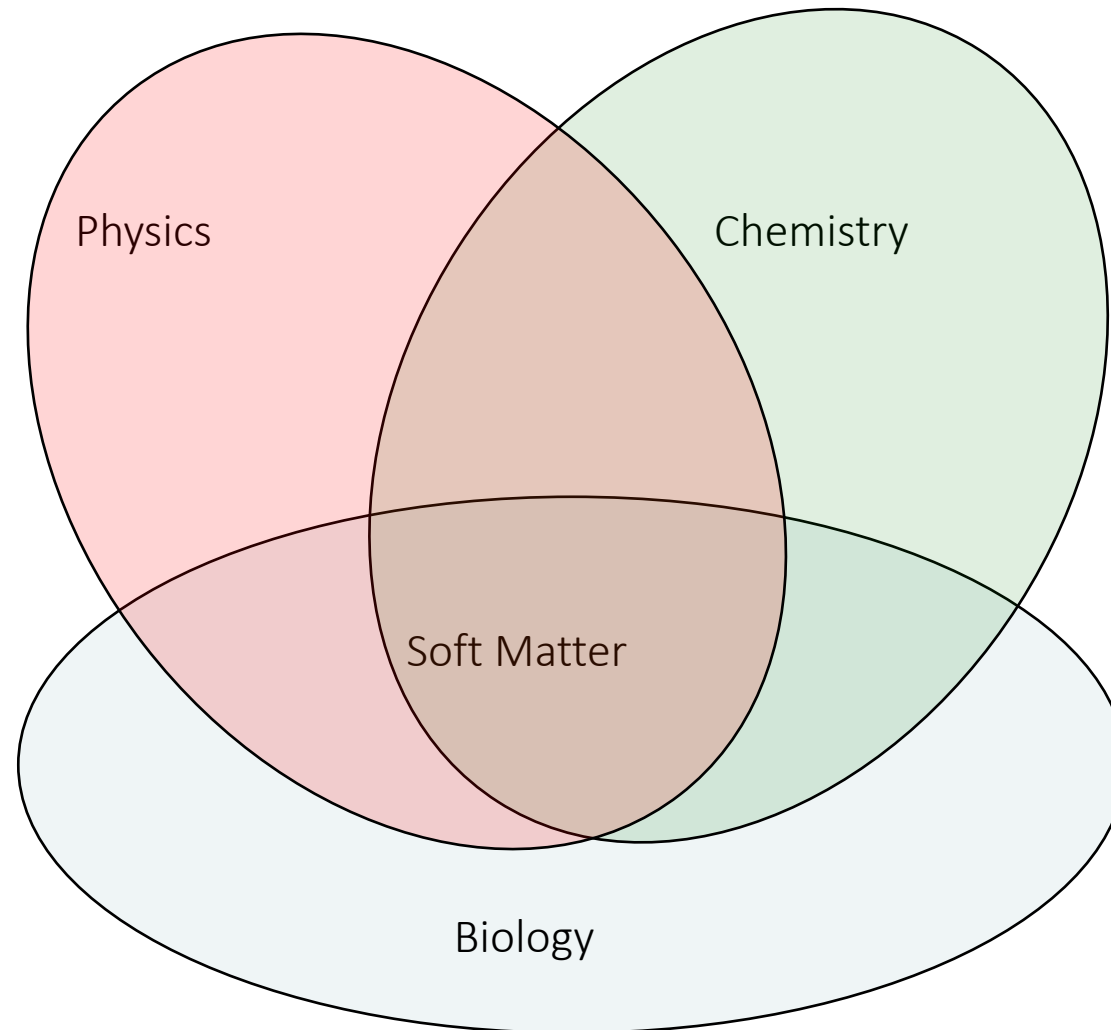
....and why is it interesting?

What is Soft Matter?



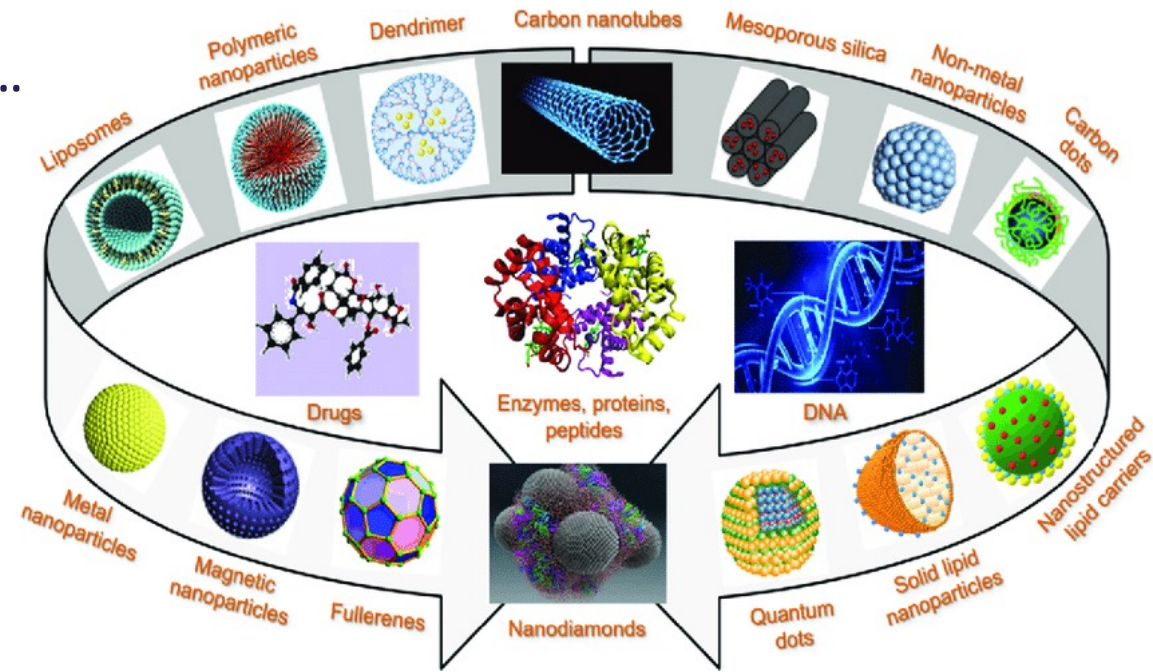
Definition of Soft Matter

Wikipedia: Soft matter is a sub-field of condensed matter comprising a variety of physical states that are easily deformed by thermal stresses or thermal fluctuations.



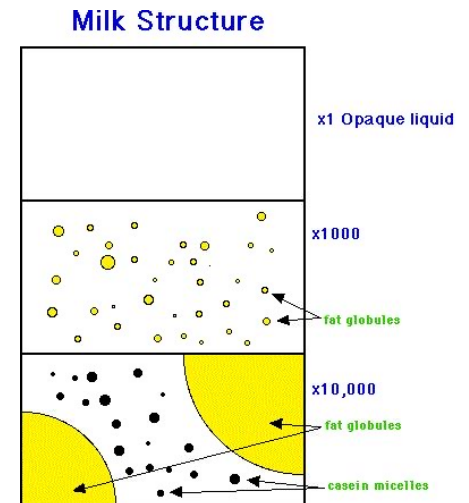
What is Soft Matter?

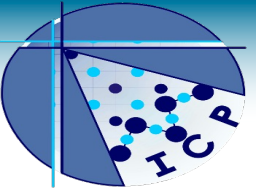
- Colloidal systems: milk, mayonnaise, paints, cosmetics...
- “Simple” plastics: yoghurt cups, many car parts, CDs, ...
- Gummy bears, gels, rubber, low fat food,
- Fibers (z.B. Goretex, Nylon)...
- Membranes: cell walls, artificial tissue, vesicles...
- Many parts of the cell, cytoskeleton, nucleus
- Most biomolecules (RNA, DNA, proteins, amino-acids)
- Liquid crystals, magnetic gels and fluids (MSM)



R. Kanwar et al., *Green Nanotechnology-Driven Drug Delivery Assemblies*, ACS Omega, 2019, doi:10.1021/acsomega.9b00304

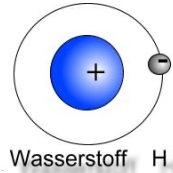
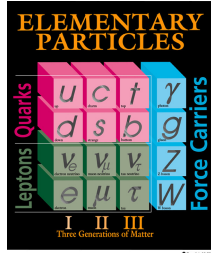
• Many applications: smart materials (actuators, sensors, photonic crystals), biotechnology, biomedicine (hyperthermia, drug targeting, cell separation techniques), energy materials, model systems for statistical physics





Length Scales of Soft Matter

1 fm 1 pm 1 Å 1 nm 10 μm 1 mm 1 m 1 km 10³ km 10⁶ parsec

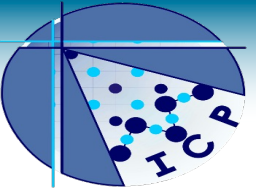


Soft
Matter



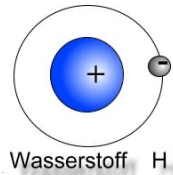
10⁻¹⁵m 10⁻¹²m

10⁻⁹m 10⁻⁶m 10⁻³ m 10⁰m 10³m 10⁶m



Length Scales of Soft Matter

1 Å 1 nm 10 μm 1 mm

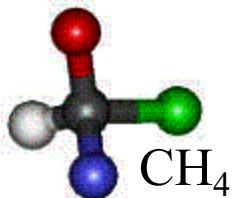
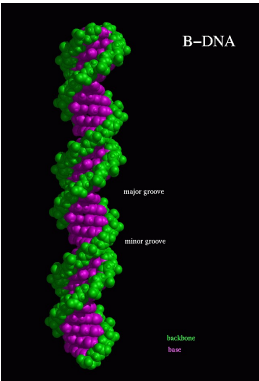


Soft Matter

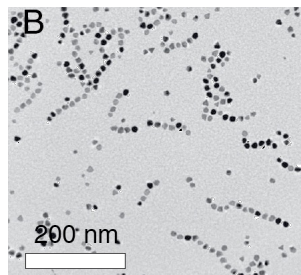
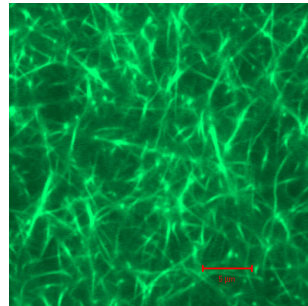


$10^{-15}m$ $10^{-12}m$ $10^{-9}m$ $10^{-6}m$ $10^{-3}m$ 10^0m 10^3m 10^6m

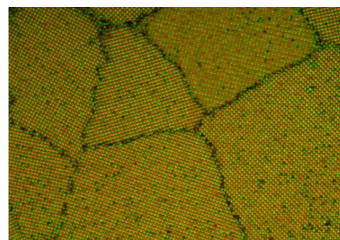
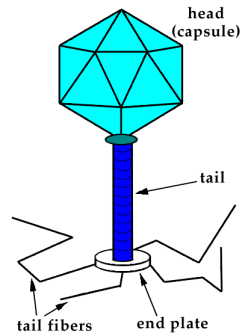
1 nm



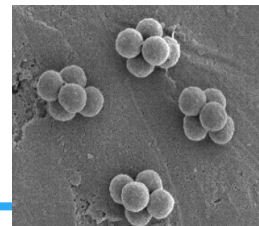
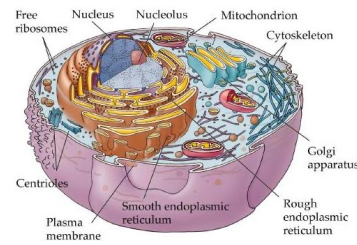
10 nm



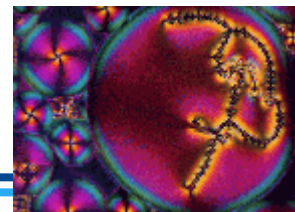
100 nm



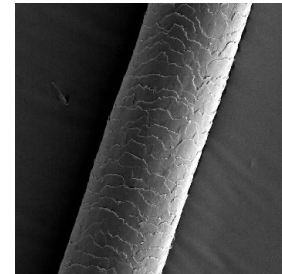
1 μm

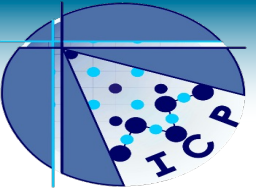


10 μm



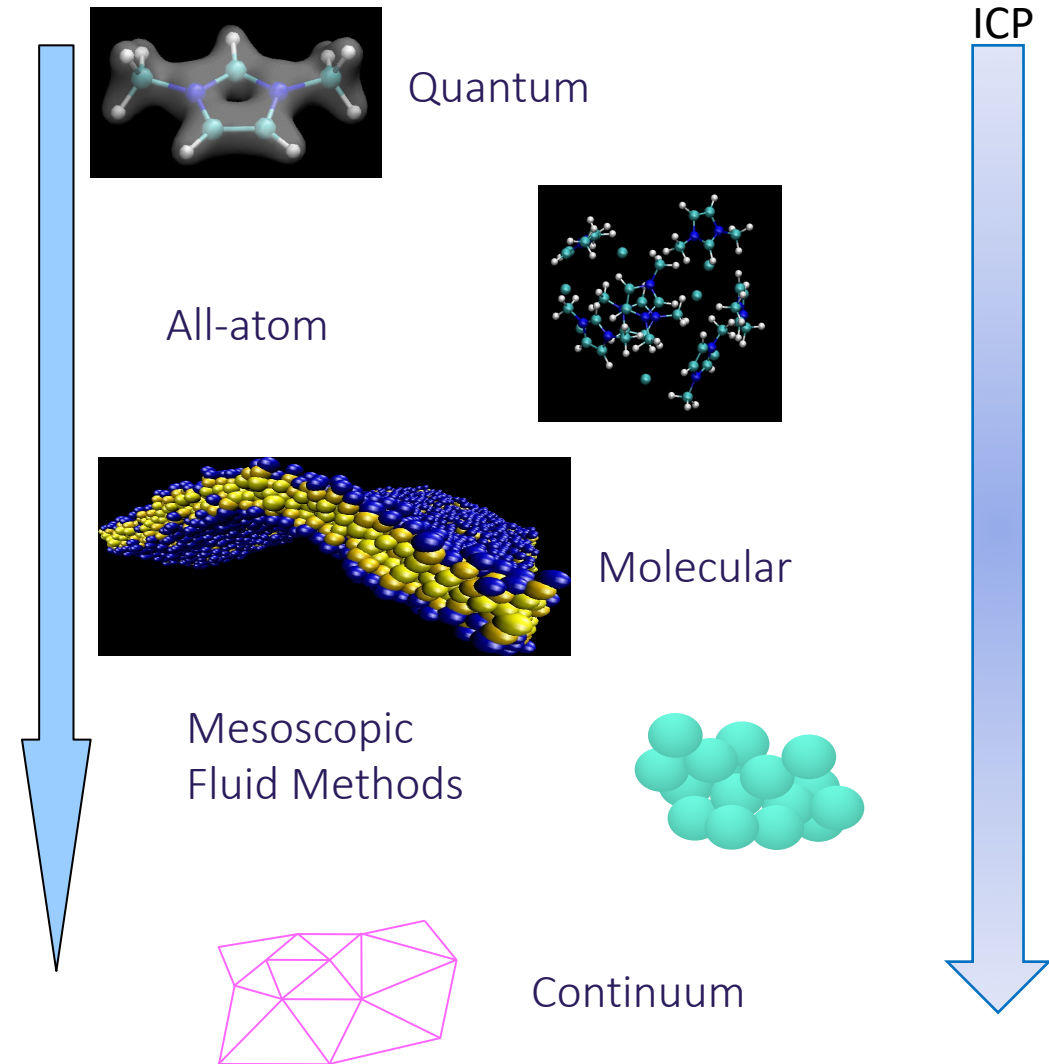
100 μm





Coarse-graining for Soft Matter Systems

- A model consists of a number of **degrees of freedom** (e.g. atomic positions: translation) and the “**interactions**” between them.
- Coarse-graining:
 - reduce the number of degrees of freedom by keeping only the “important” degrees of freedom,
 - use “effective” interactions
- Classical first step: Atoms and Interactions (*all-atom* or *atomistic*)
- Further coarse-graining is often needed and useful
- For Soft Matter we are often on the molecular and mesoscopic level



Members of Various Research Consortia

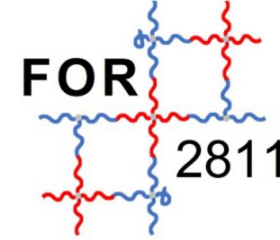
SFB 1313 "Interface-Driven Multi-Field Processes in Porous Media – Flow, Transport and Deformation"



SFB 1333 "Molecular Heterogeneous Catalysis in Confined Geometries"



FOR 2811: Adaptive Polymer Gels with Model-Network Structure



Multi-scale
EuroHPC Centre of Excellence



Nanopore technology for the molecular diagnostics of the future



Cluster of Excellence
EXC 2075



With funding from the:



[CECAM Node Soft Matter and Statistical Mechanics \(SMSM\)](#)

Current Research Fields

Computational Methods and Algorithms

- **ESPResSo (parallel MD package)**
- Lattice-Boltzmann for coarse-grained hydrodynamics
- Reaction-Diffusion systems (FEM) for Catalysis
- ML strategies for developing better FF for MD
- ML assisted Coarse-graining strategies
- Understand Neural Network learning strategy
- QML or ML for physics applications

Biophysical Problems

- Macromolecular complexes
- Nanopore sequencing and separation techniques
- Targeted drug delivery
- Properties of peptides and DNA

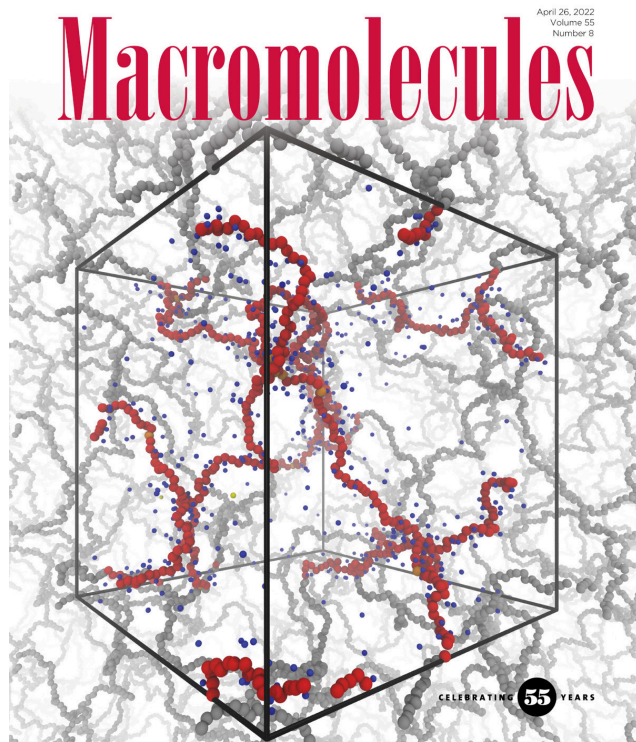
Soft Matter Problems

- Better Batteries (Electrodes, Fluids)
- Active Matter and SPPs
- Charged macromolecules
- Hydrogels
- Magnetic colloids and ferrogels
- Transport properties of ions and charged macromolecules in porous media



ESPResso school
2025 at the ICP

www.espressomd.org



ACS Publications
Most Trusted. Most Cited. Most Read.

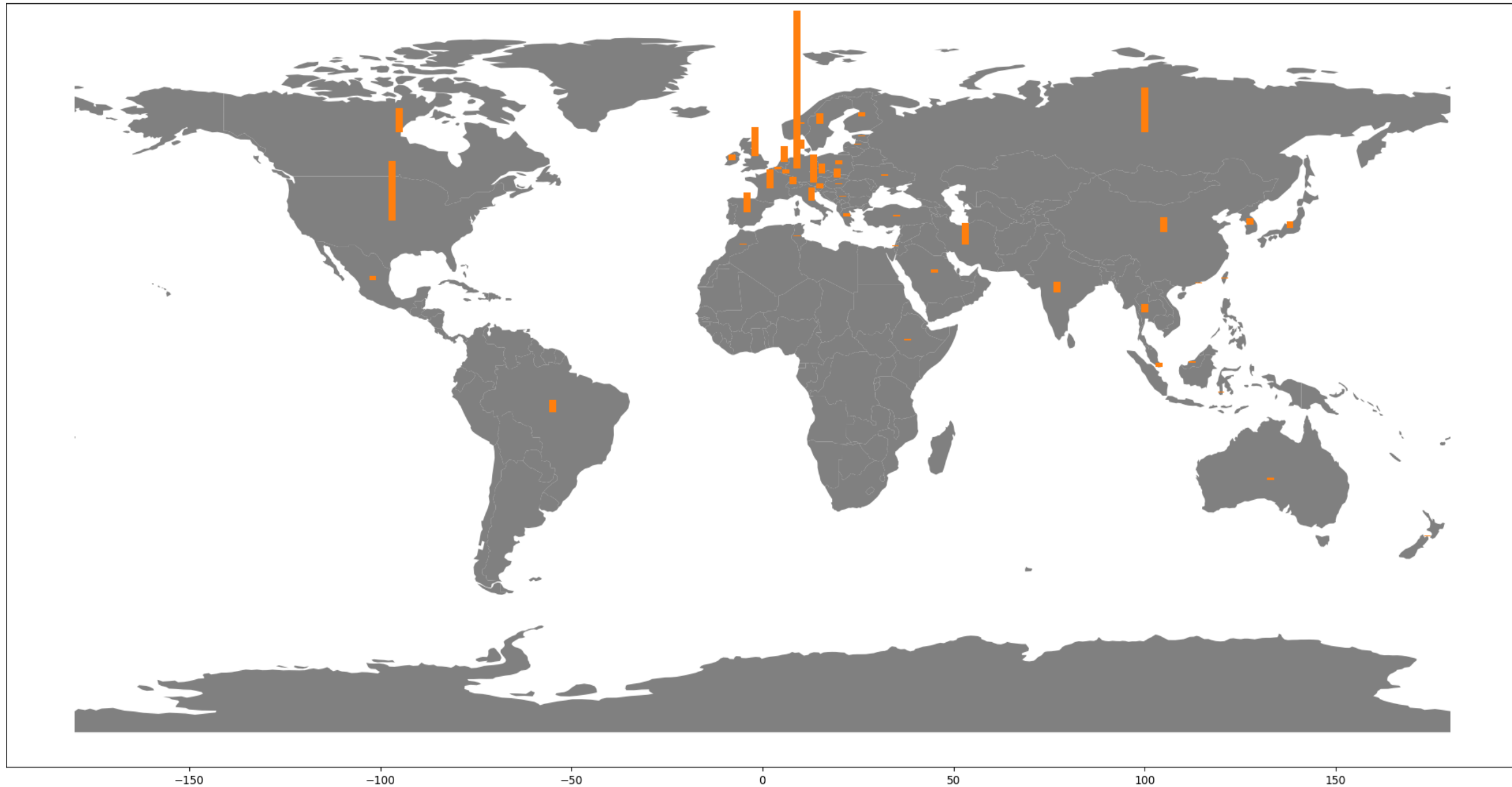
www.acs.org



ESPResso is a highly versatile software package for performing and analyzing scientific **Molecular Dynamics** many-particle simulations of **coarse-grained** atomistic or bead-spring models as they are used in **soft matter research** in physics, chemistry and molecular biology. It can be used to simulate systems such as polymers, liquid crystals, colloids, polyelectrolytes, ferrofluids and biological systems, for example DNA and lipid membranes.

Talk to Rudolf Weeber weeber@icp
or Jean-Noel Grad jgrad@icp

World Map of ESPResSo Users

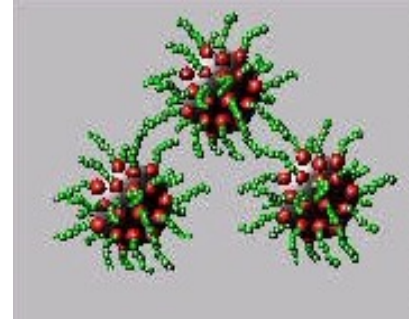


Magnetic Soft Matter

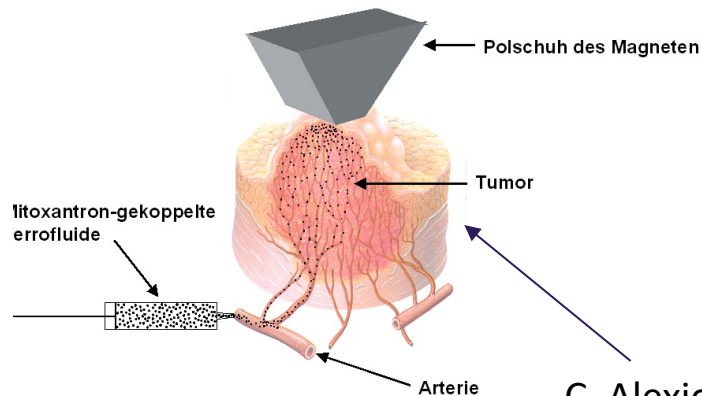
- **Magnetic particles suspended in a carrier:**
- **Ferrofluids:** live in a liquid carrier
- **Ferrogels:** have a gel as carrier
- The investigated magnetic nanoparticles:

size ~ 10 nm

single ferromagnetic domain with a permanent dipole moment
(superparamagnetic)



Prinzip der lokalen Chemotherapie mit
Magnetischem Drug Targeting



C. Alexiou (HNO- Klinikum Erlangen)

Applications:

mechanical (*sealing of rotating shafts*);

thermal (*cooling of loud speakers*);

medical (*cancer treatment, hyperthermia, magnetic cell separation*)

Ferrofluids can be influenced via magnetic fields

A microscopic image showing a dense cluster of small, dark, rod-like particles, likely ferrofluid particles, arranged in a circular pattern. The particles are oriented vertically, suggesting they are aligned with a magnetic field. The background is light and slightly blurred.

Structure Formation in Ferrofluids

Magnetic Gels

- Hydrogels are polymer networks swollen by a carrier fluid
- Magnetic gels additionally contain magnetic nanoparticles
- Using an external field, the shape and elasticity can be controlled

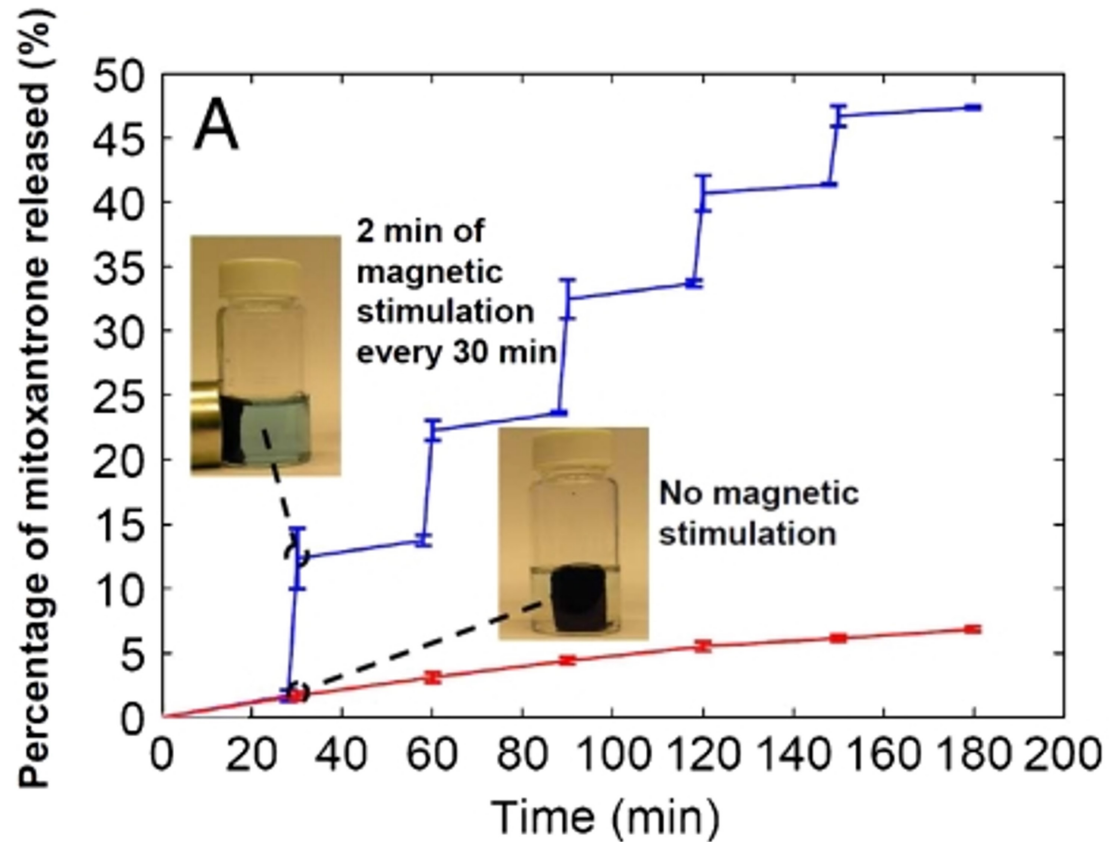
Magnetic gels

Shape-Programmable Magneto-Active Elastomers Composites
for Curve and Biomimetic Behavior Imitation

Supporting Movie 2

Biomimetic Deformation Behavior of MAEs Composite
Mimicking Wing-Flapping of Birds

Drug Release From Magnetic Gels



- It is possible to enclose a drug within the magnetic gel
- Using an external field, the release of the drug can be controlled

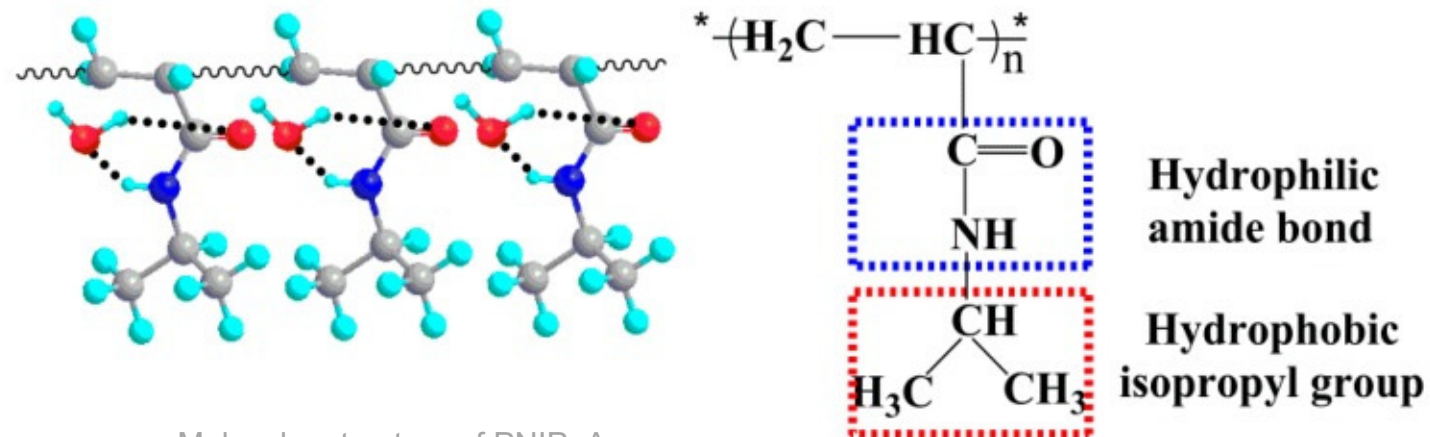
Possible Thesis Topics

- Model the loading and release of drugs from magnetic gels
- Understanding the influence of inhomogeneities in the network on experimentally observable properties

Coarse-graining and Machine-learned Potentials

Creating a Coarse-grained Model for Thermo-reversible Polymers

- Some polymers change their properties drastically with temperature
- For example, PNIPaAm collapses when driven over the lower critical solution temperature
- This can be modelled using atomistic simulations, but they are costly
- In the thesis, an approximate coarse-grained model should be generated which allows simulating bigger systems



Molecular structure of PNIPaAm.
Yang L, Fan X, Zhang J, Ju J. Polymers (Basel), 2020

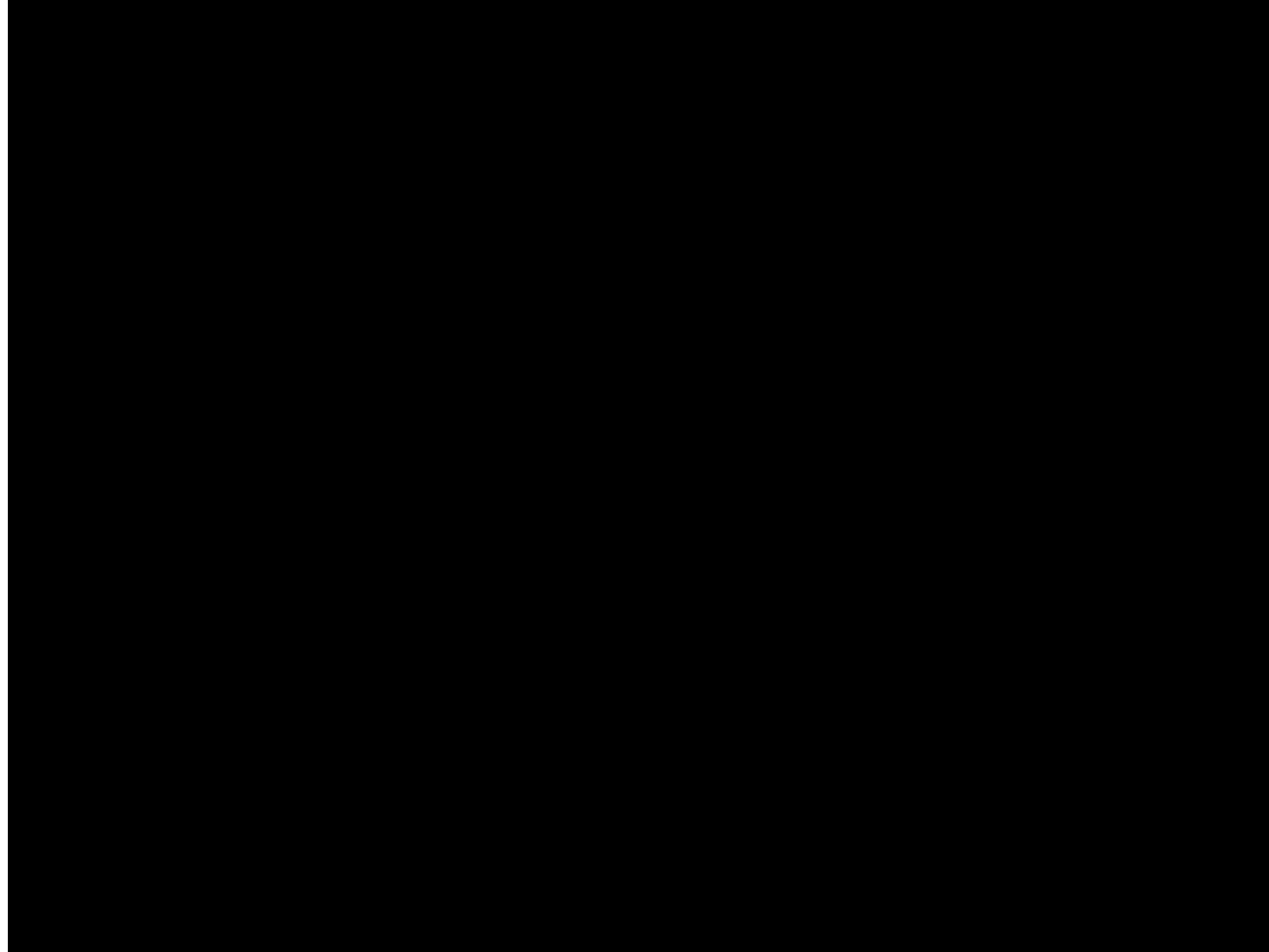
Viscoelastic Fluids

Viscoelasticity

Viscoelastic materials combine properties of a fluid and a solid:

- They are viscous like fluids: stress proportional to shear rate
- But also elastic like solids: stress proportional to shear amplitude

Viscoelasticity

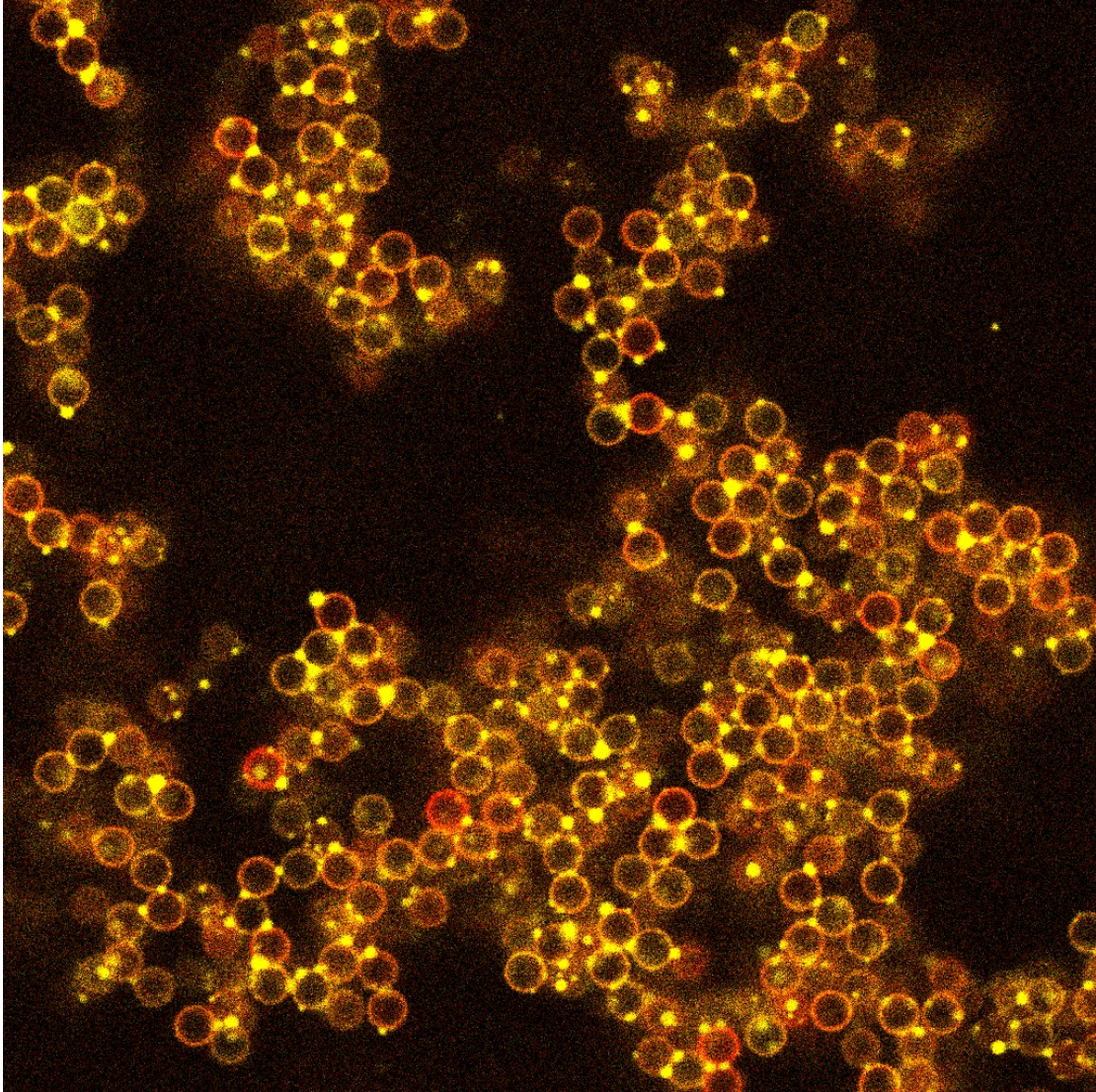


Viscoelasticity with Thermal Fluctuations

- Goal of the project is to extend an existing solver for a viscoelastic fluid to thermal fluctuations
- We will use this to look at self-propelled particles in viscoelastic media
- The project has a significant analytical component

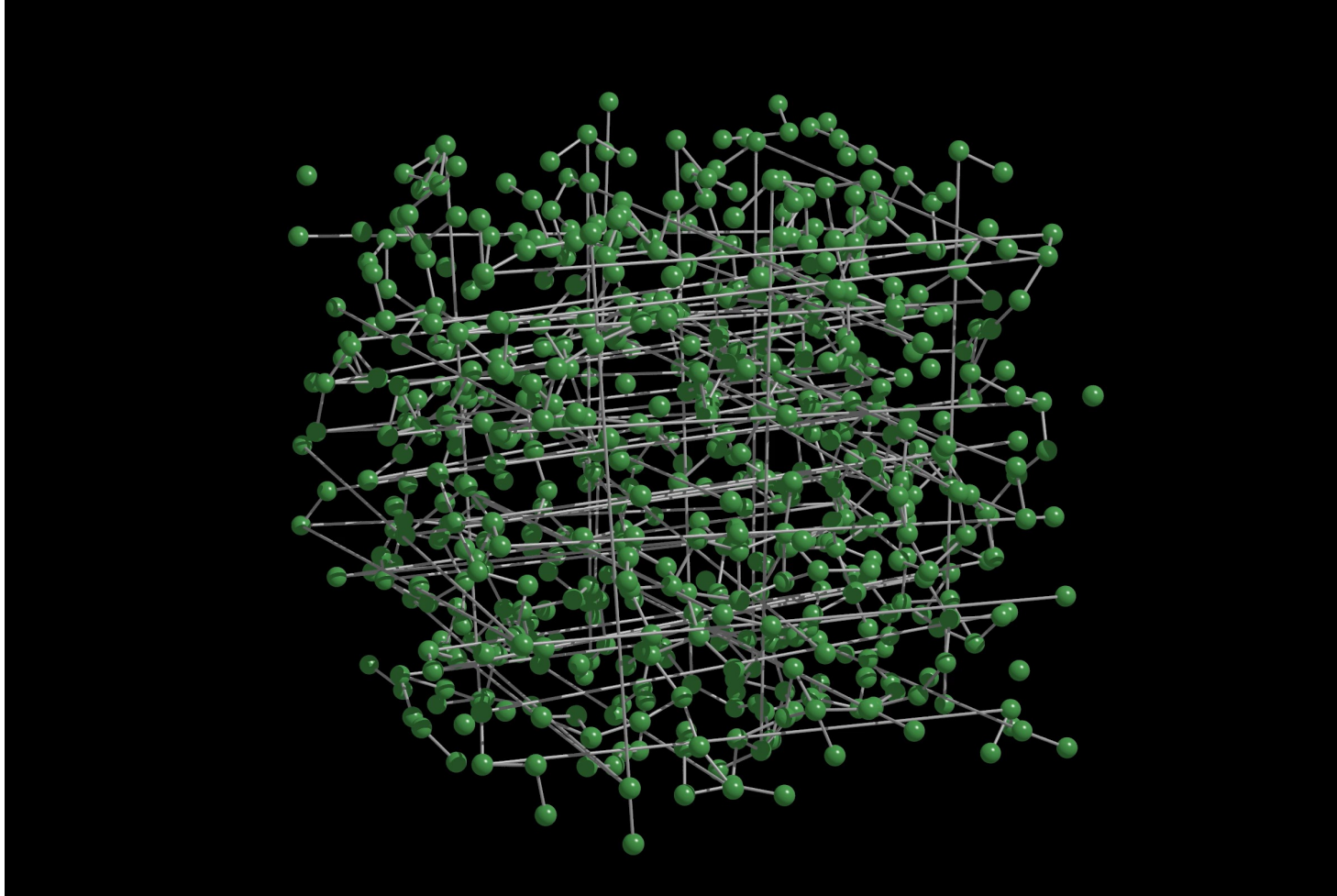
Capillary Suspensions

Capillary Suspensions



- A small amount of immiscible fluid is added to a colloidal suspension
- It forms capillary bridges between the colloidal particles, forming a network
- The suspension becomes highly viscoelastic

Capillary Suspensions

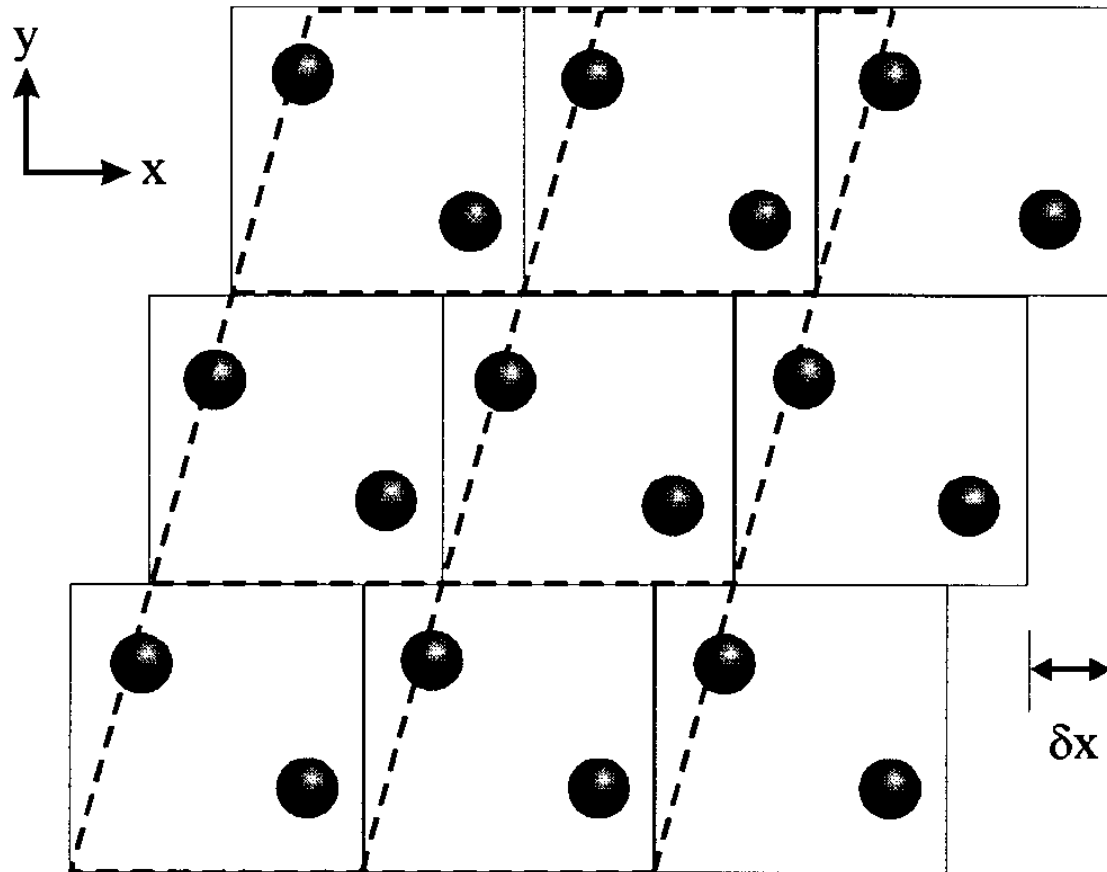


System under oscillatory shear.

- In the project, we will study the break-up of this network under shear

Electrostatics Under Shear

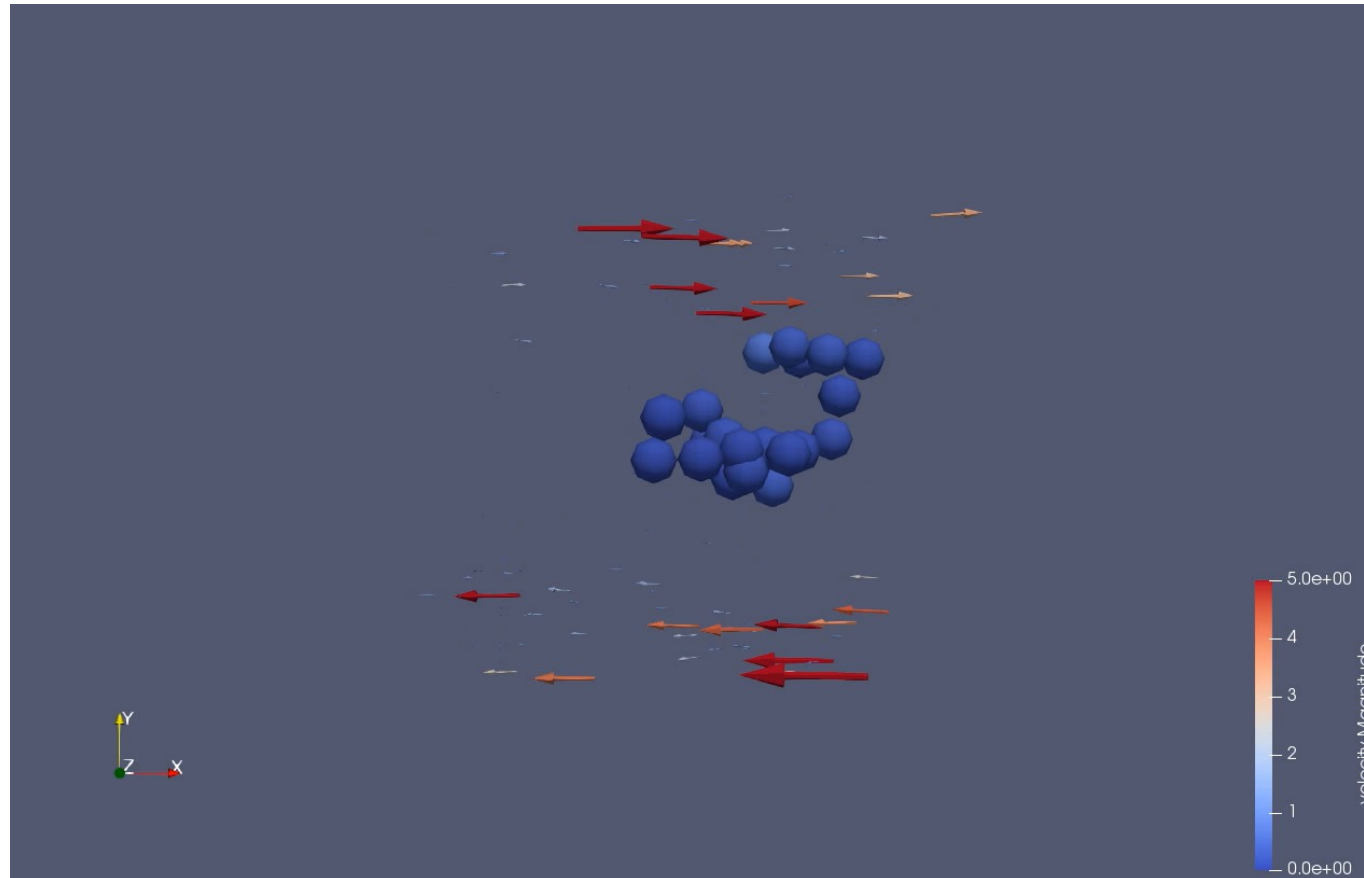
Electrostatics Under Shear



- The flow properties of a system are studied by applying shear in a viscosimeter and measuring the resulting stress
- We can do this in simulations using Lees-Edwards boundary conditions
- In the project, the P3M electrostatics solver will be extended to support this

Electrostatics Under Shear

- We will then explore, how a polyelectrolyte suspension behaves under shear

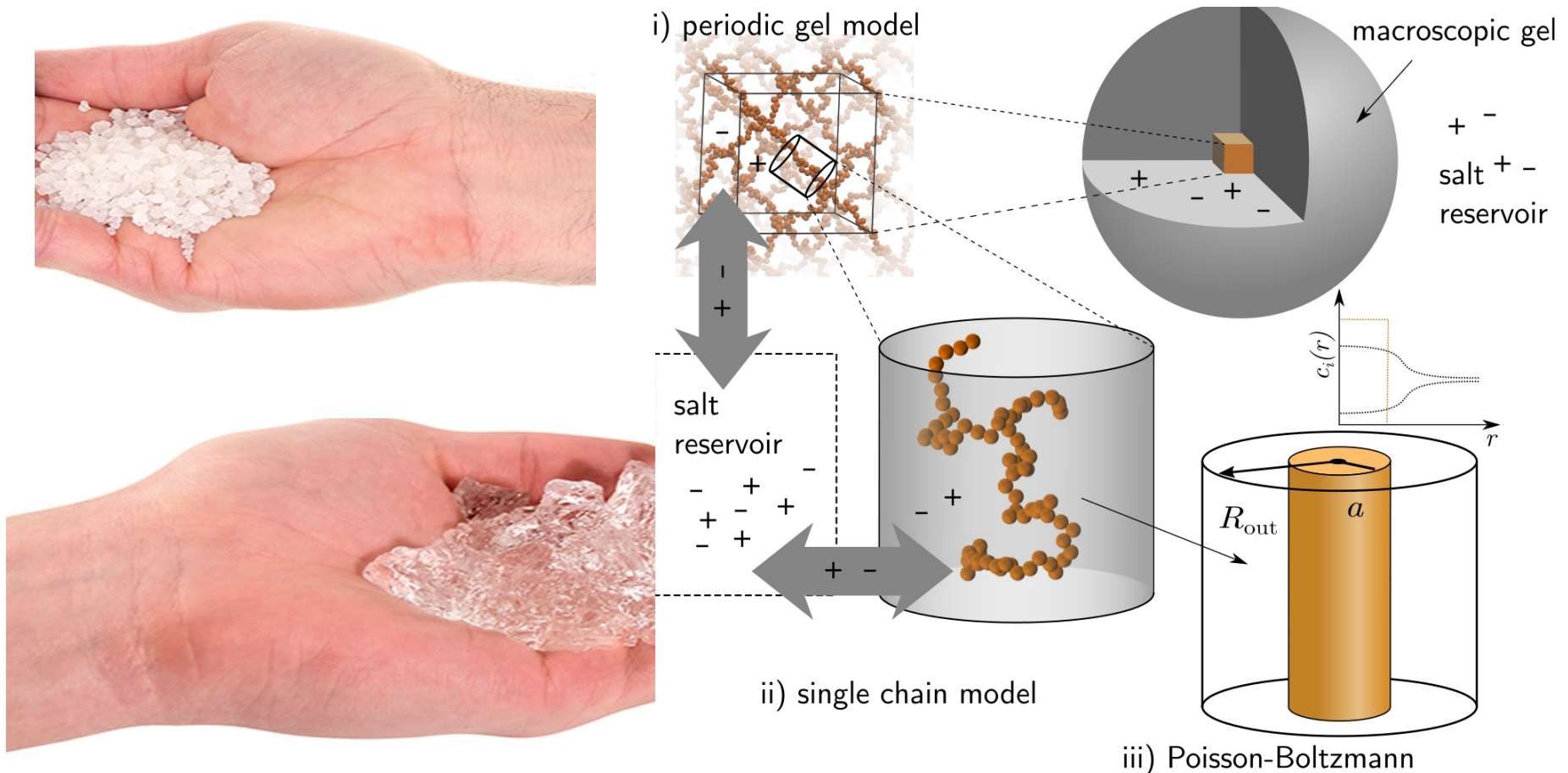


Polymer in a shear flow.

Hydrogels: Smart Functional Materials

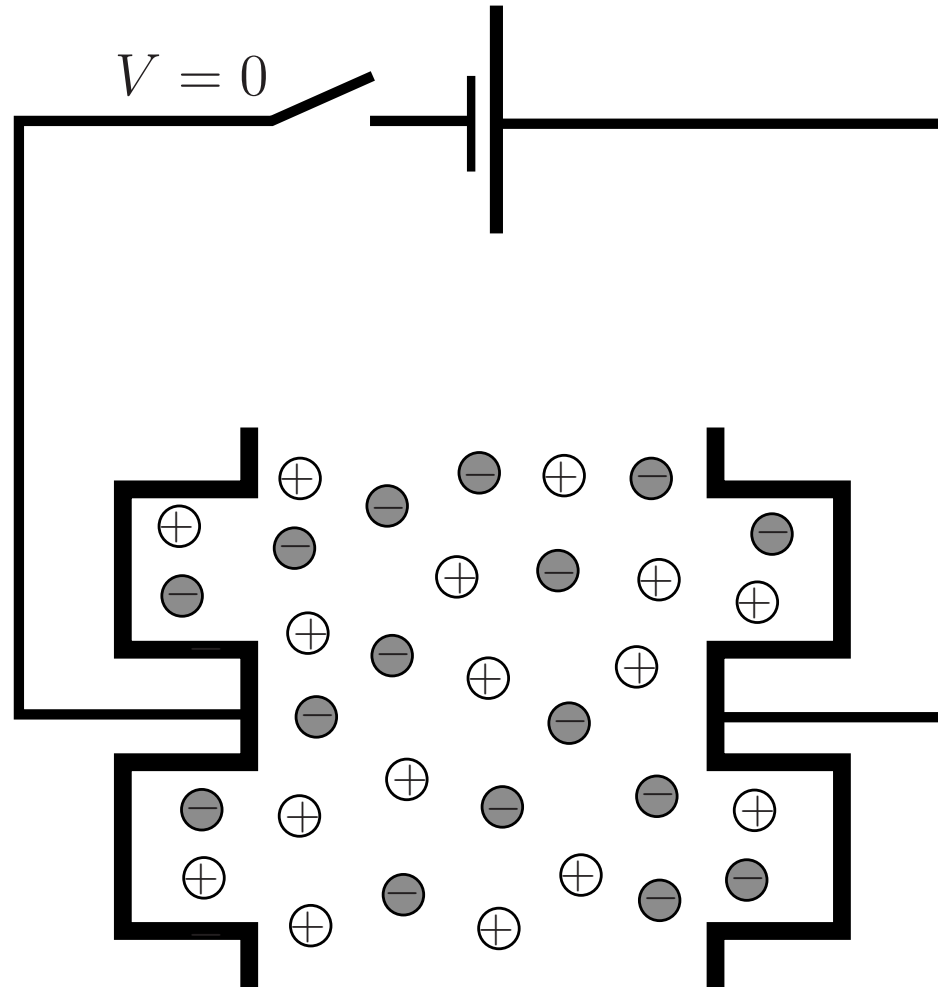


Modeling Approaches for Hydrogels on Different Levels

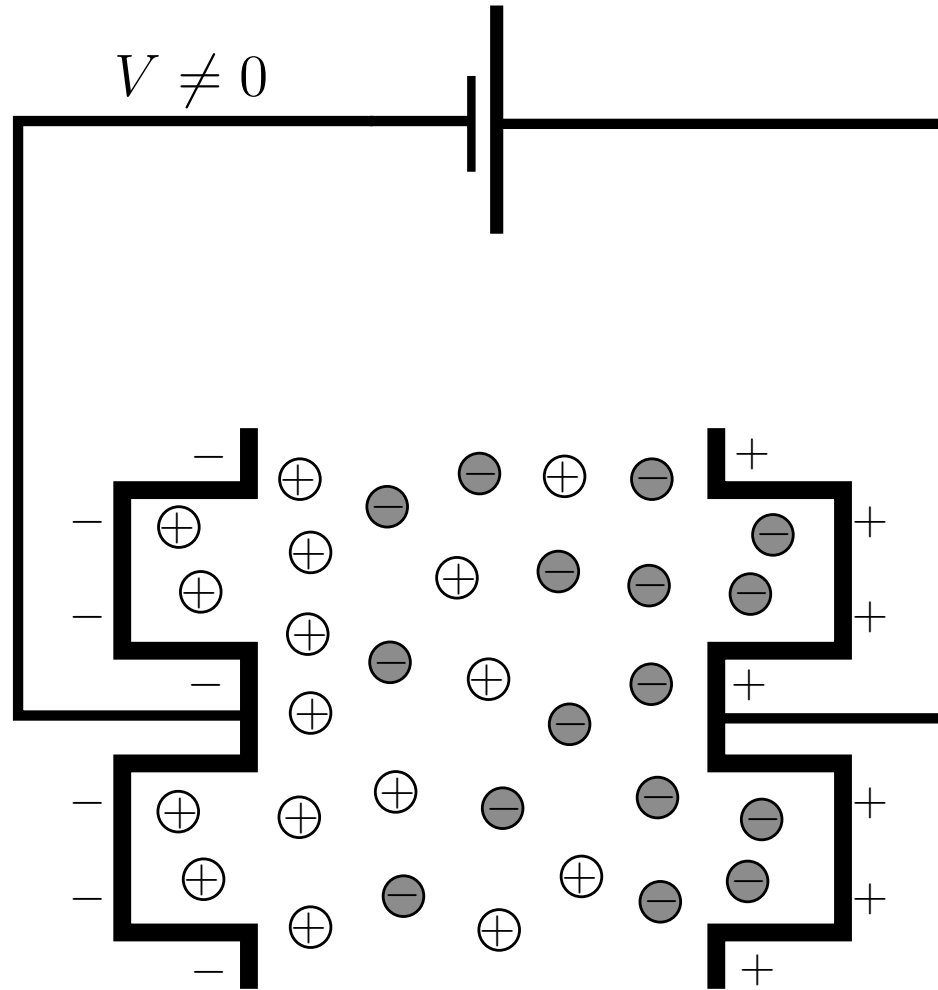


Supercaps

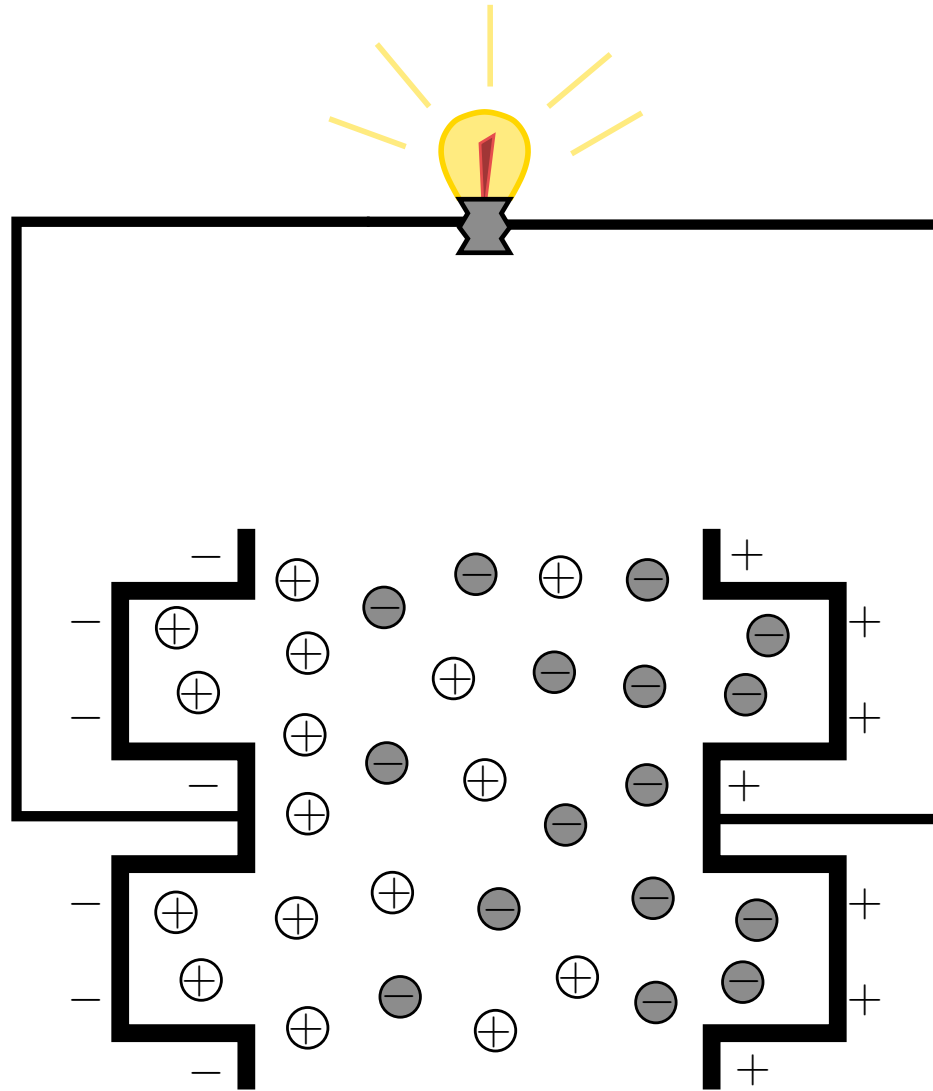
What is a Supercapacitor



What is a Supercapacitor

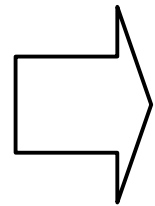


What is a Supercapacitor

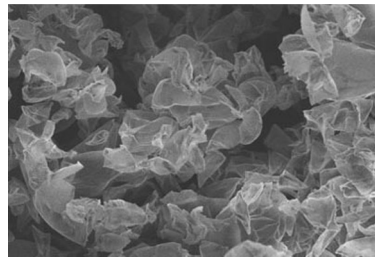


Application to Supercapacitors.....

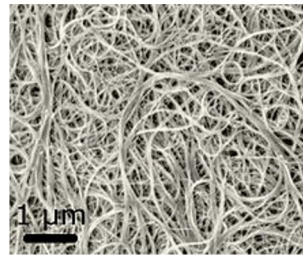
Supercapacitors are used for mobile energy storage in Electric Double Layer Capacitors / “Supercapacitors” with high specific capacitance. “Fast and Furious??”



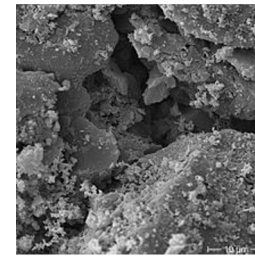
High surface area electrode material (>1000 m²/g)



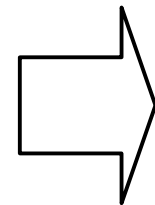
Curved graphene sheets
Liu et al., Nano Lett. (2010)



Carbon nanotubes
https://en.wikipedia.org/wiki/Carbon_nanotube



https://en.wikipedia.org/wiki/Activated_carbon



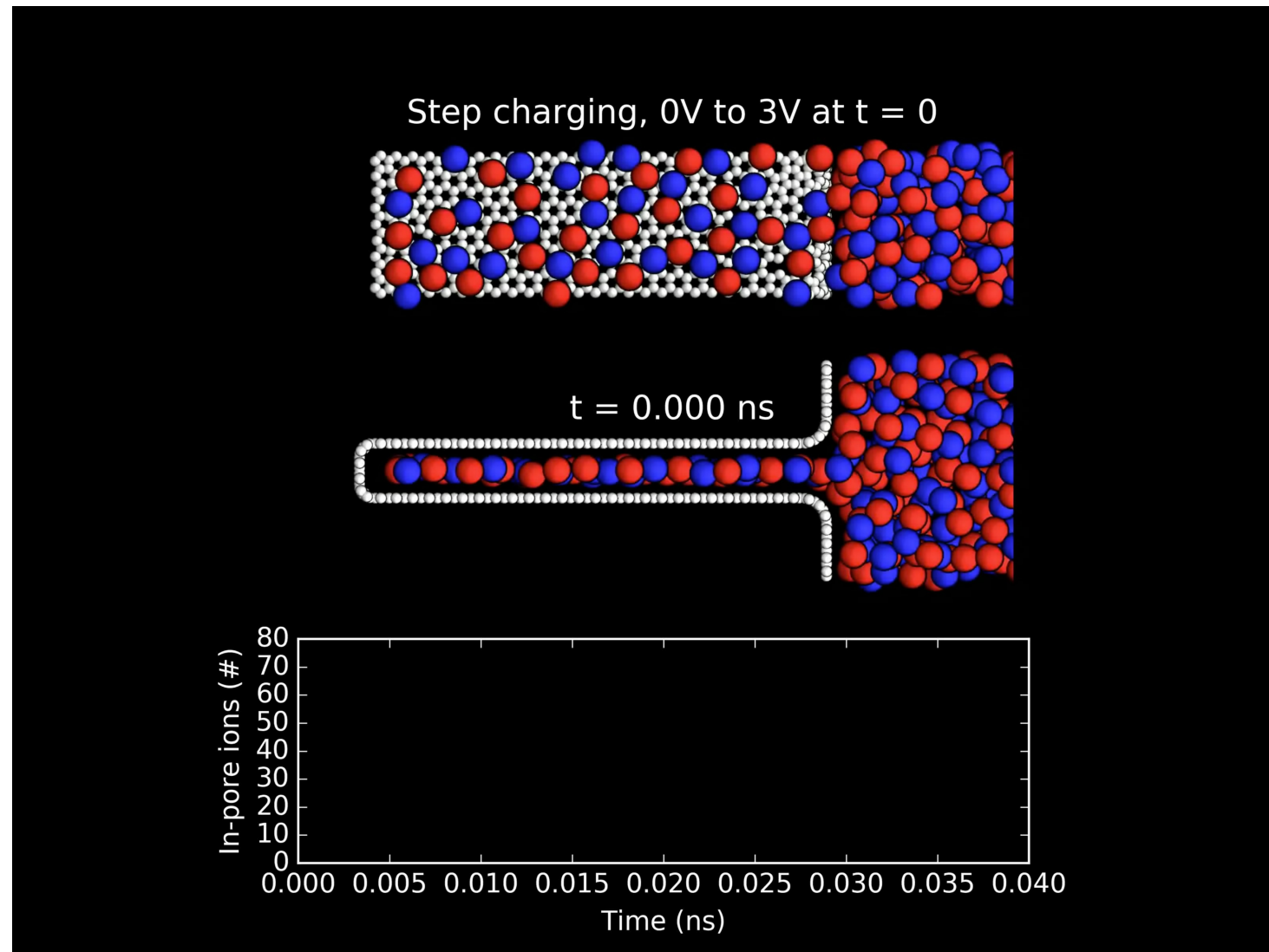
Electrolyte:

- Aqueous (e.g. Water + KOH or H₂SO₄)
- Organic solvent + Salt
- Ionic liquids

Our Goal

Understand charging mechanisms and ion dynamics in narrow charged pores for simple model systems

Voltage sweep speeds up charging of a capacitor



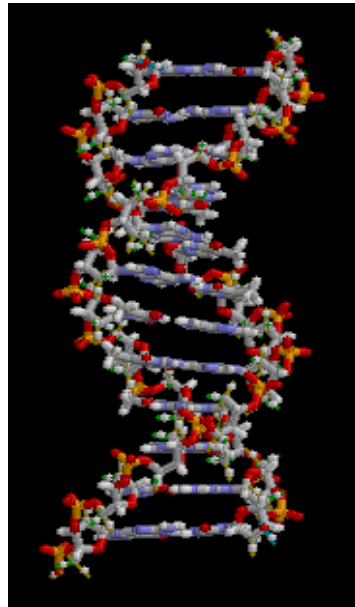
Breitsprecher, Holm, and Kondrat. "Charge me slowly, I am in a hurry: Optimizing charge–discharge cycles in nanoporous supercapacitors." ACS nano 12.10 (2018): 9733-9741.

Nanopore Sequencing

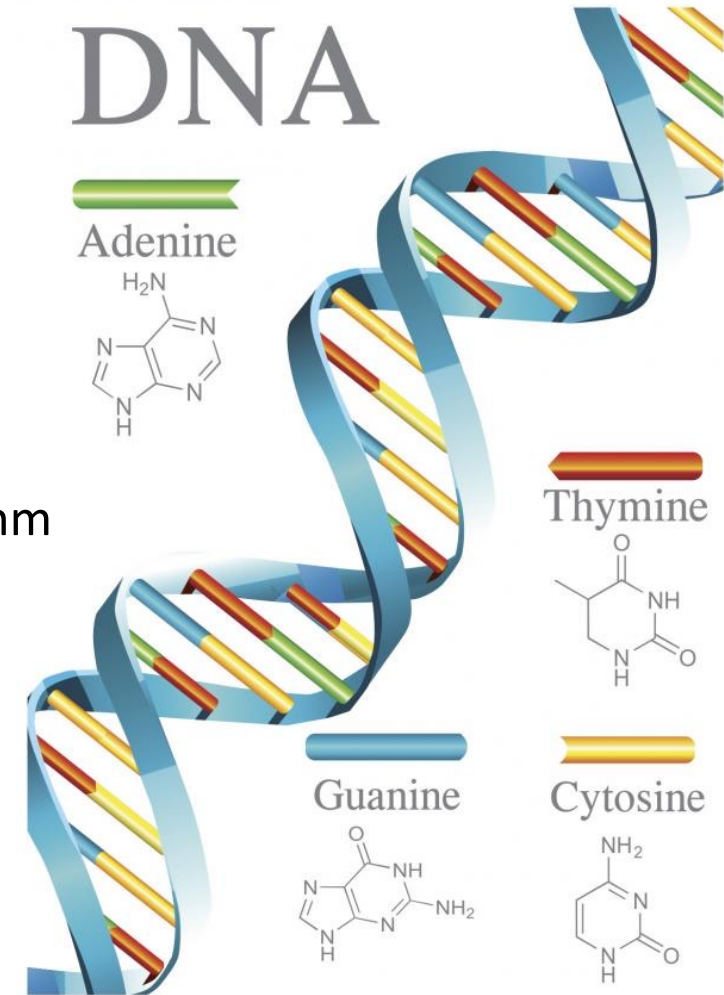
DNA Facts

dsDNA is a charged biopolymer, consisting of paired bases yielding the form of a double helix in water.

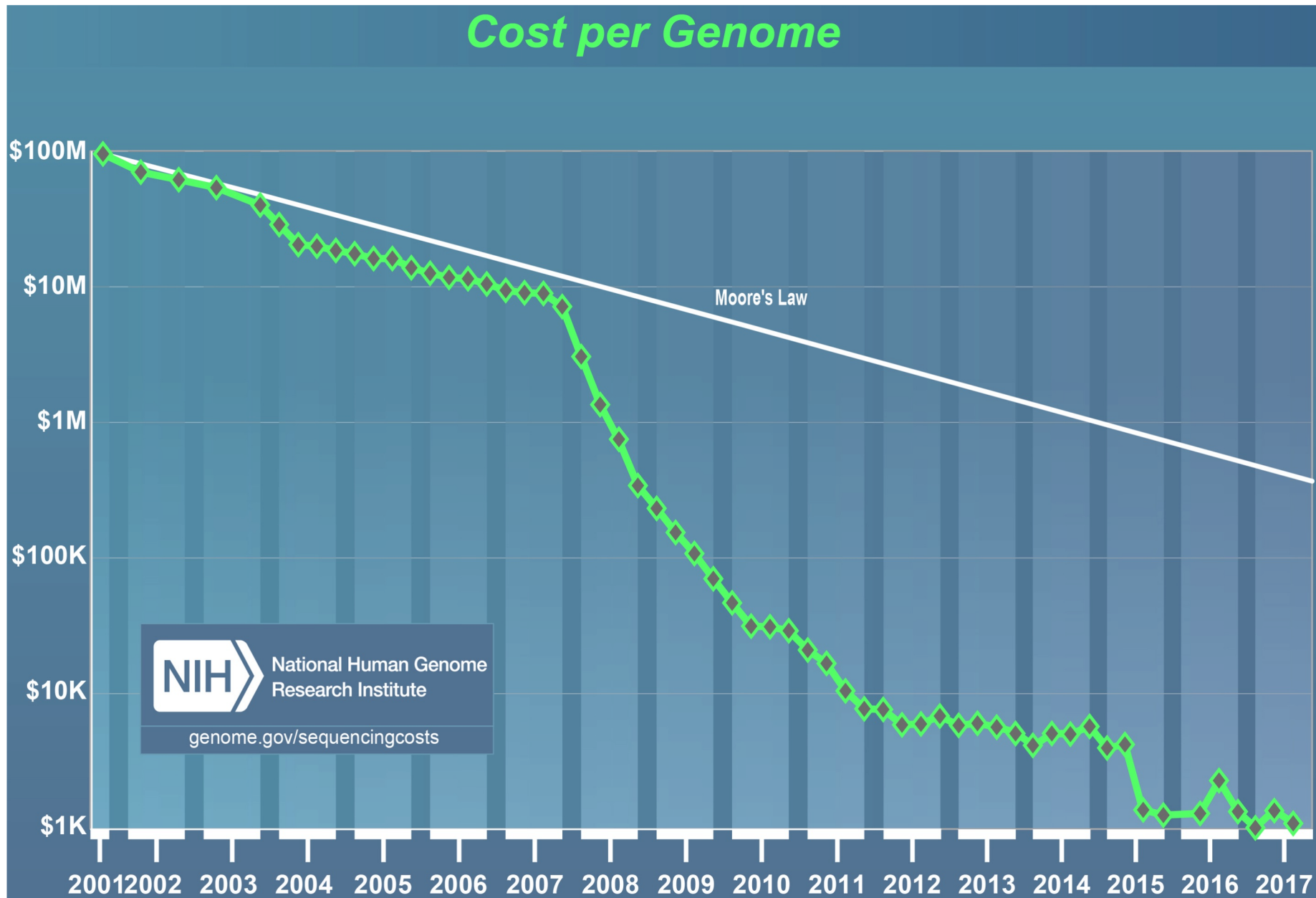
The sequence of either strand encodes our genetic information which we want to read out.



persistence length $l_p=50\text{nm}$



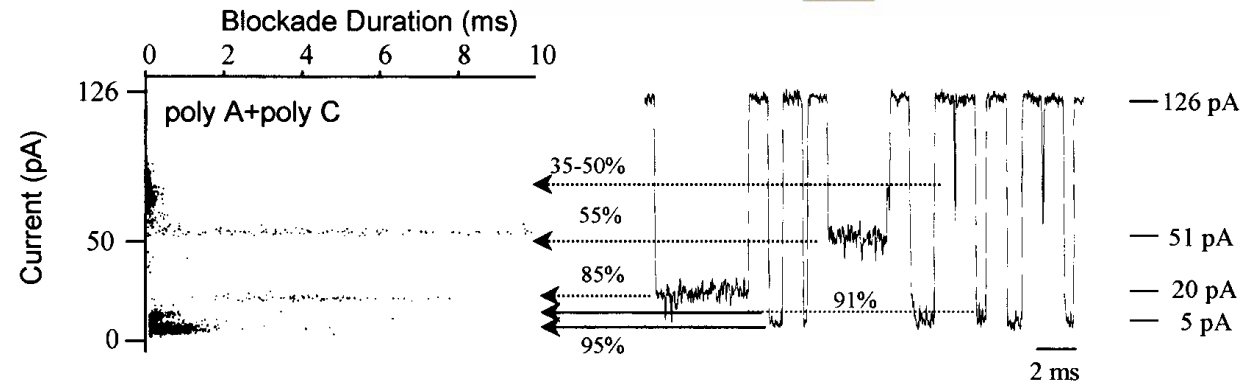
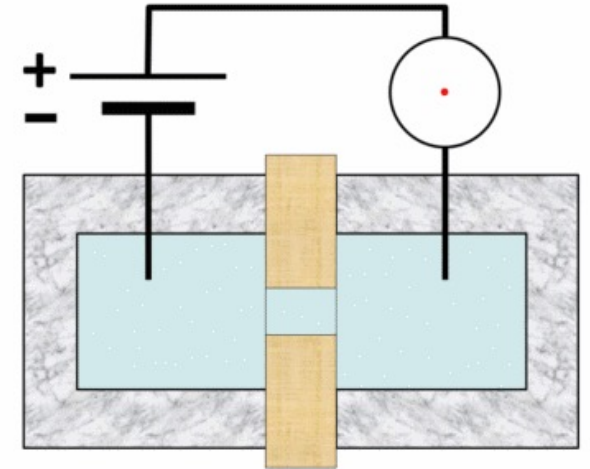
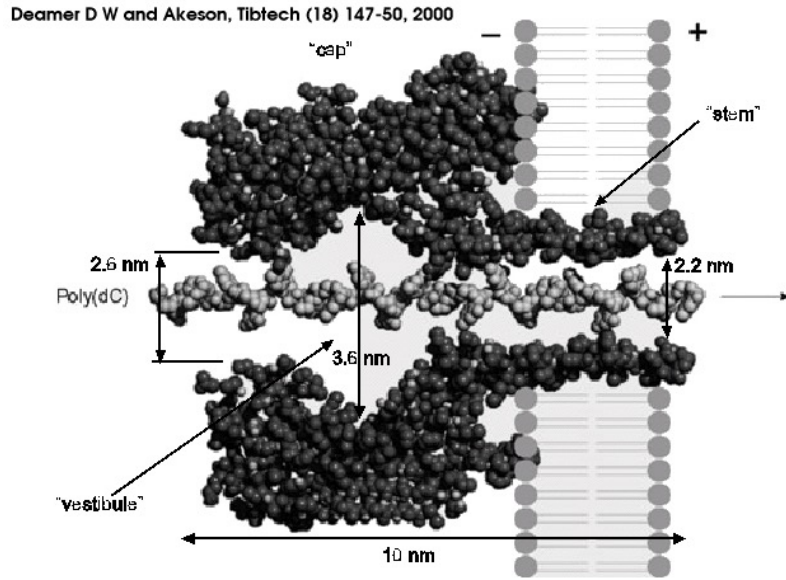
Costs of DNA Sequencing



Nanopore Sequencing Approach

- acts like a more refined Coulter counter for blood cells

Electric Field

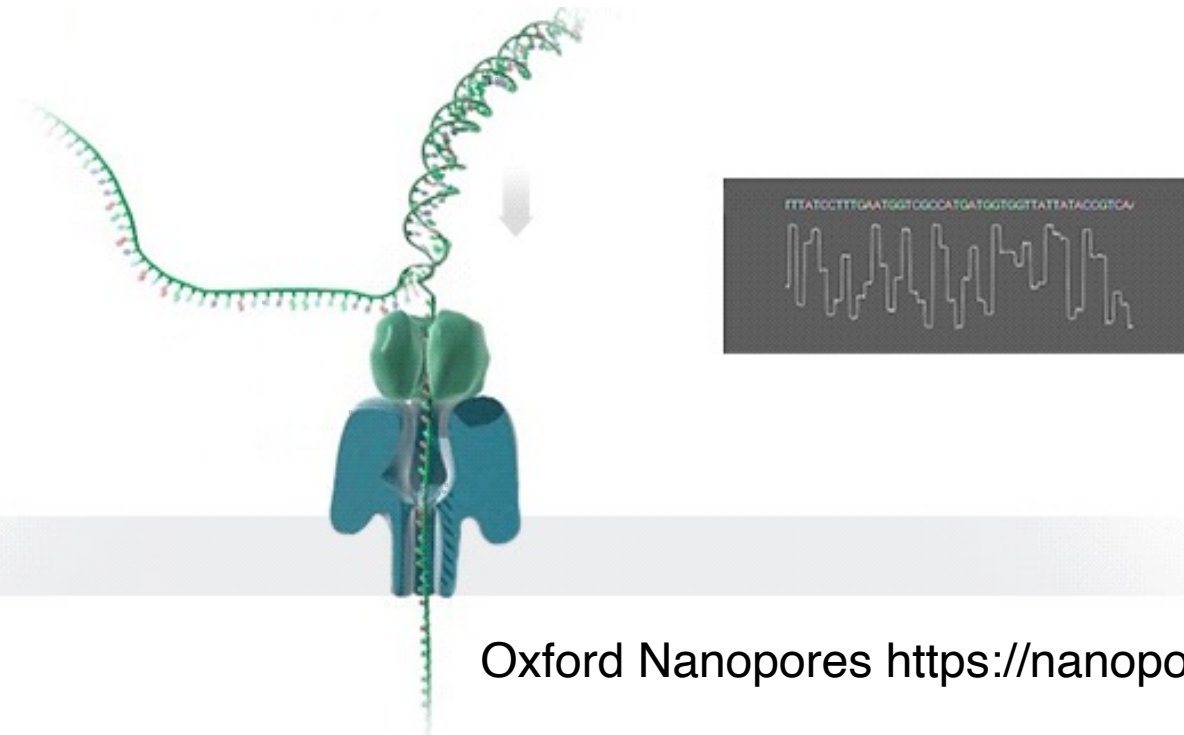


Electric Current

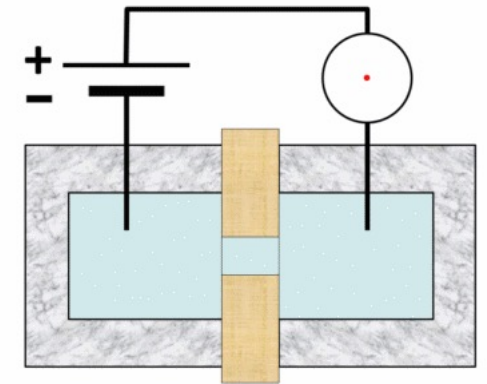
- conductivity measurements can reveal bp translocation of ssDNA
- Recognition of binding sites of proteins to DNA

ML Approaches for optimizing Nanopores

- acts like a more refined Coulter counter for blood cells

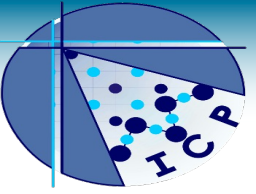


Oxford Nanopores <https://nanoporetech.com>

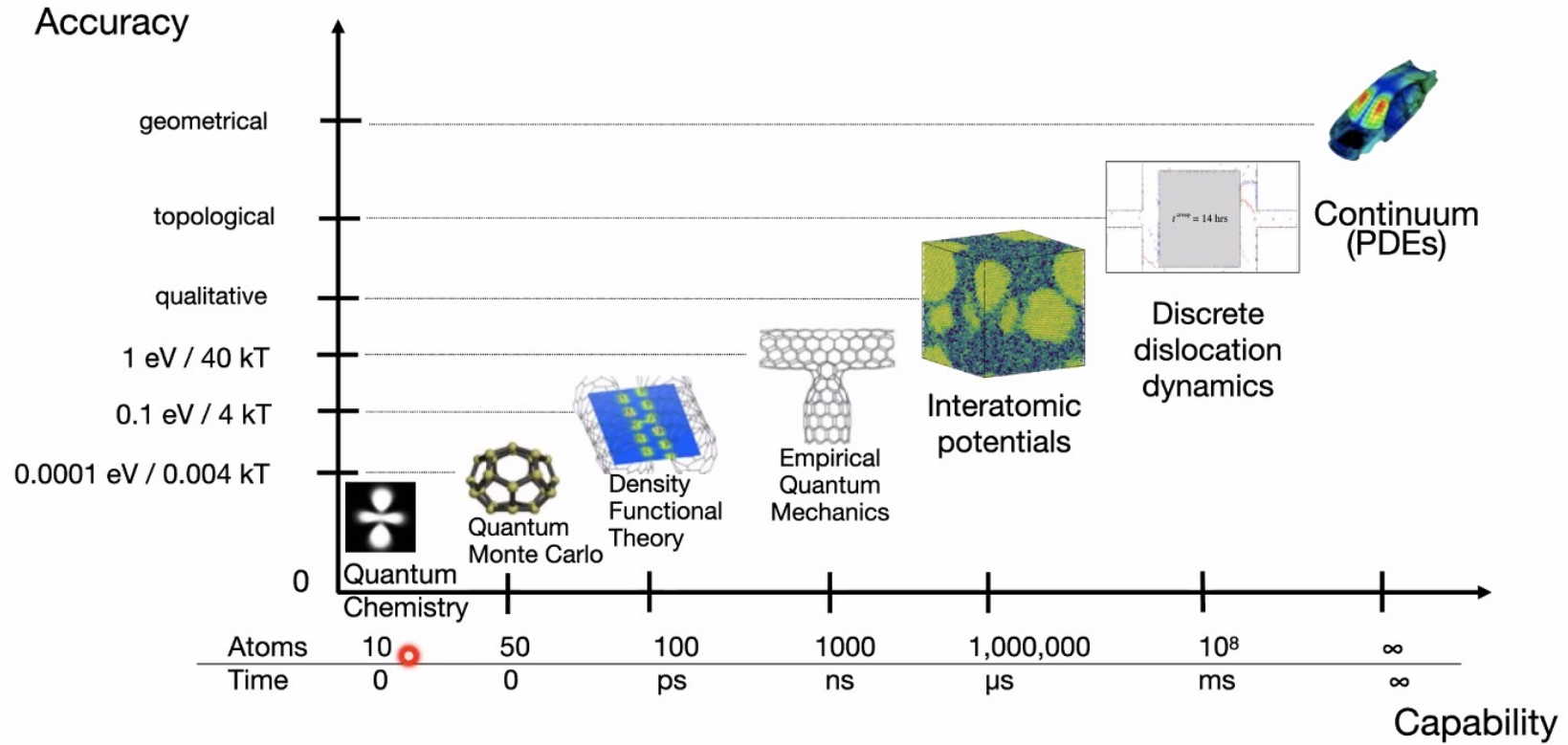


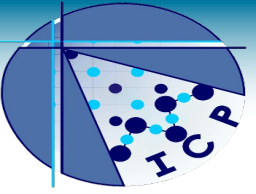
- Use ML approaches to optimize the current readout to recognize protein sequences from real experimental data provided by collaborators from Freiburg using a different biological nanopore (Aerolysine)



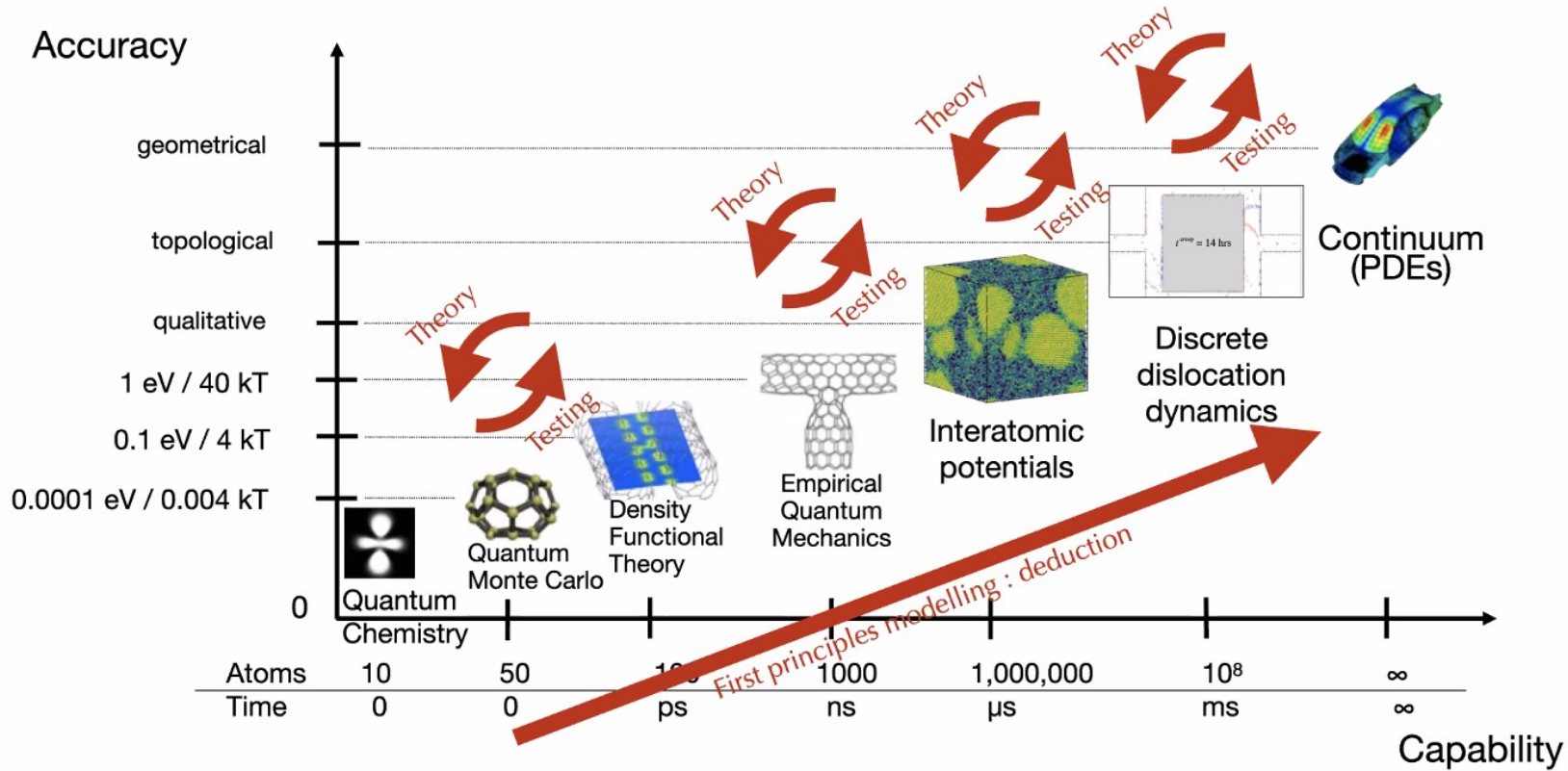


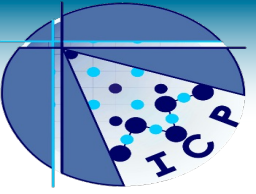
Multiple scales of materials modelling



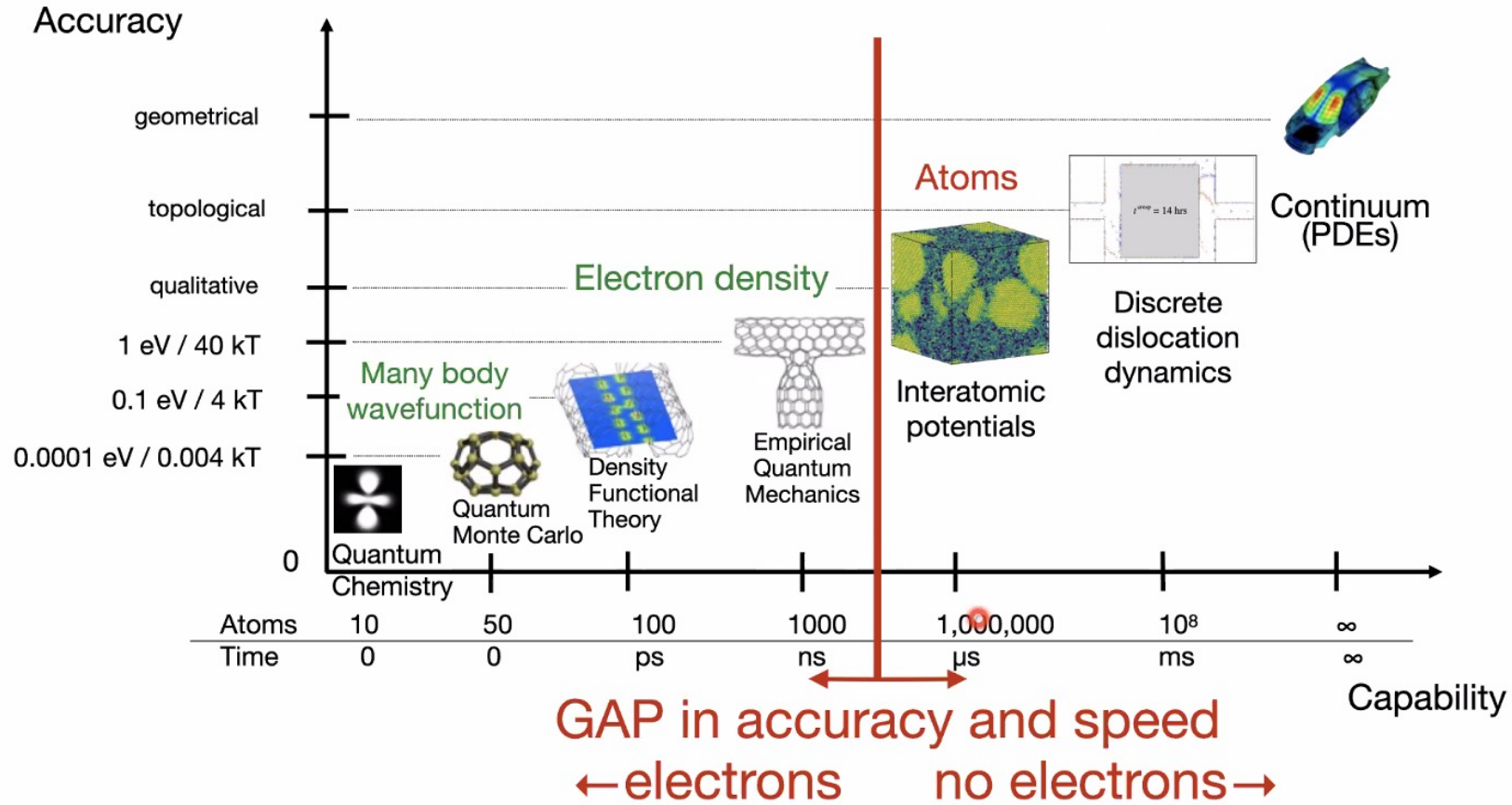


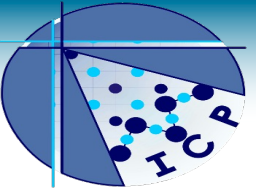
Multiple scales of materials modelling



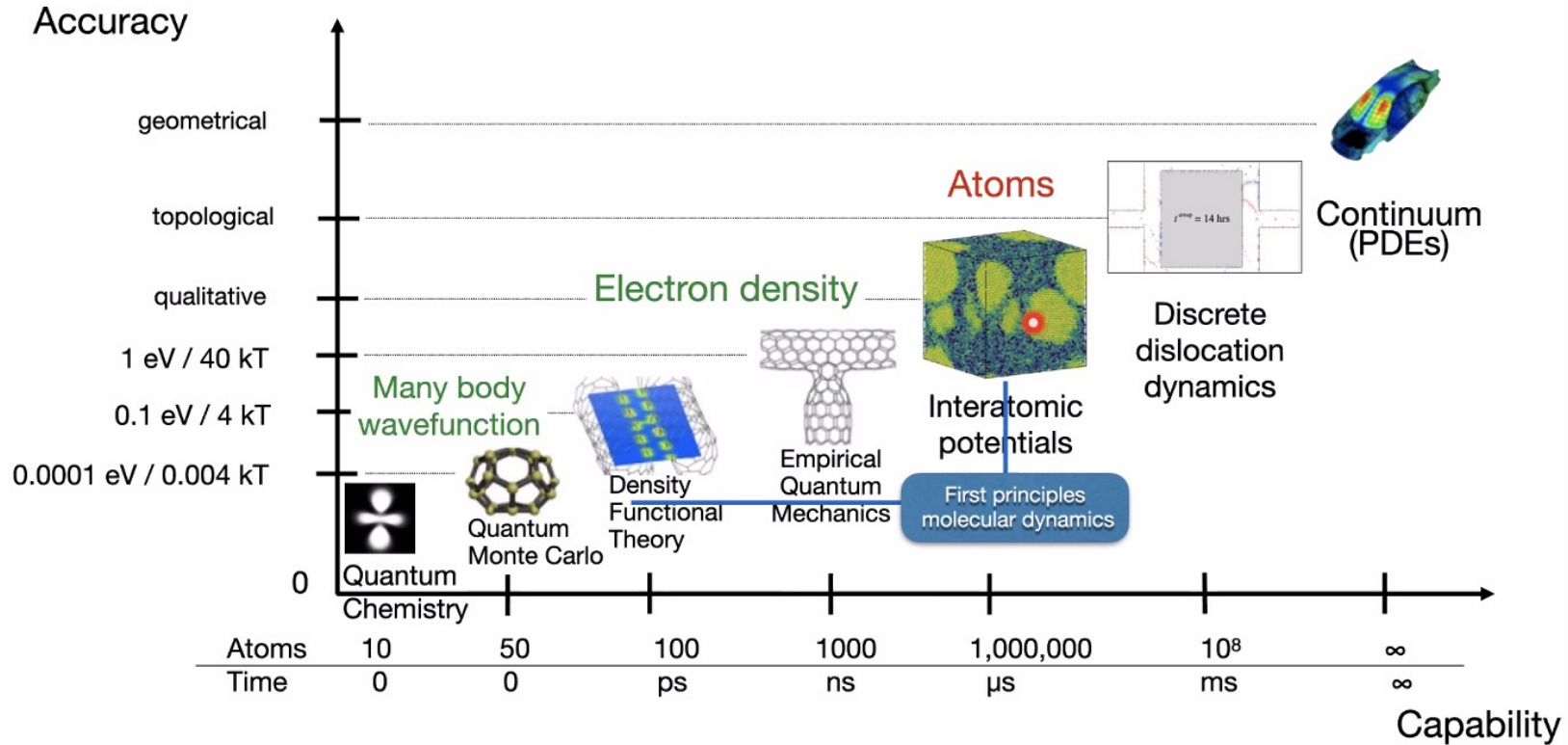


Multiple scales of materials modelling





Multiple scales of materials modelling



Machine learned interatomic potentials from ab-initio input (often DFT)

What do we expect from you?

- Be curious for new phenomena
- Be open to use the computer as your experimental platform
- Be ready to use your imagination and physical intuition
- Some familiarity with the computer expected:
- Very helpful: Python
- Helpful C++
- We also use ready to use software suits: ESPResSo, ZnTrack, MDSuite, MLSuite, MaiCos, COMSOL, GROMACS, CP2K, PyTorch, TensorFlow...

Various TOPICS Bachelor, Master, SimTech
Projects

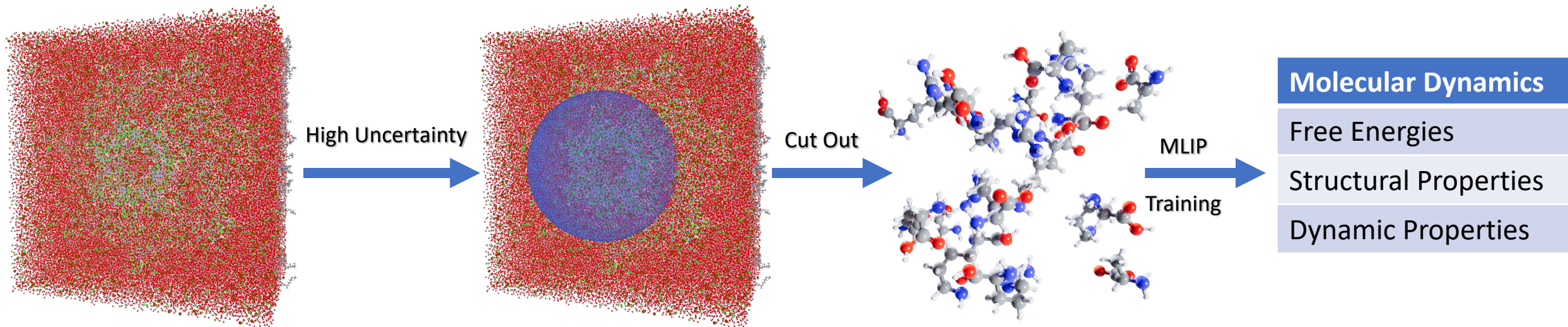
Machine-Learned Interatomic Potentials for Nanopore Protein Sequencing

Fabian Zills fzills@icp.uni-stuttgart.de

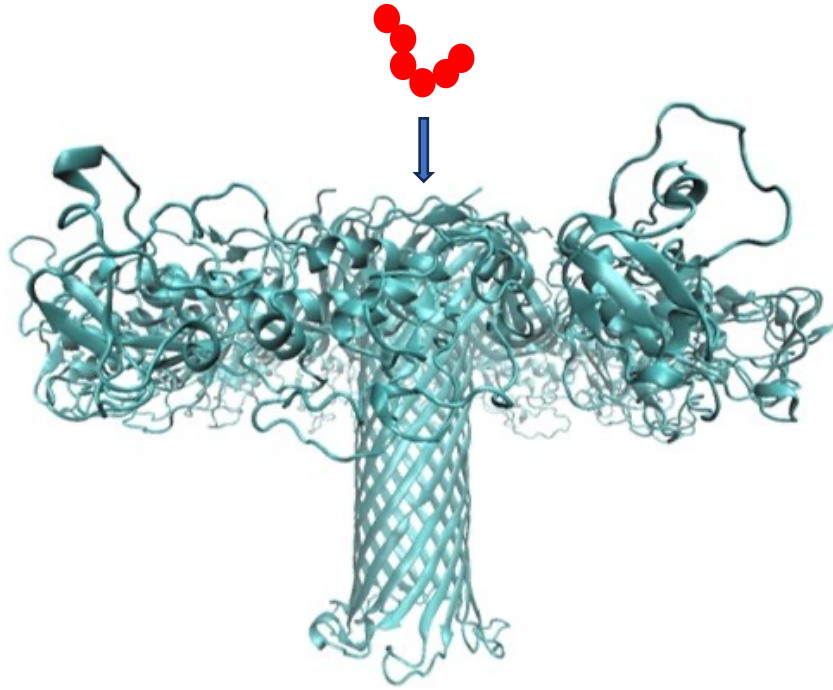
- Develop Machine-Learned Interatomic Potentials (MLIPs) for biological nanopores (B.Sc. / M.Sc.)



Utilize and **develop** state-of-the-art MLIP code
<https://github.com/zincware>

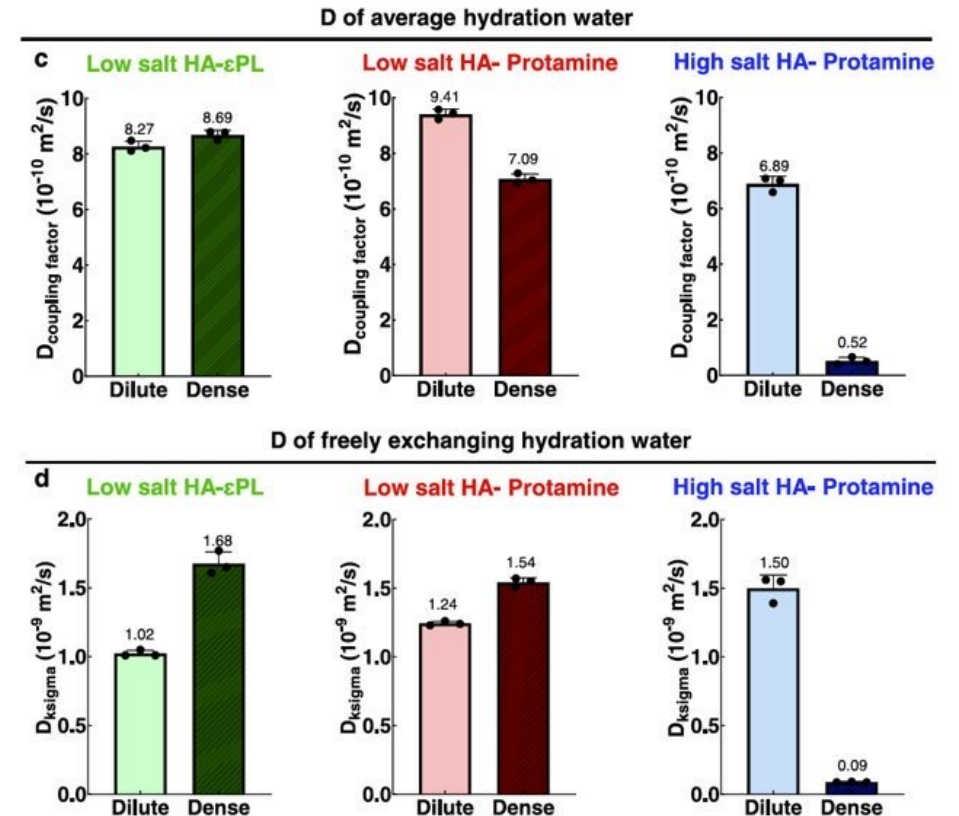


A machine-learning interatomic potential (MLIP) forcefield (FF) for charged peptides in salt solutions



Peptide enters in nanopore

Peptide dynamics in salt solution



Diffusion coefficients measured at under different exp. conditions

Work flow and dataset design

Initial structure/box construction

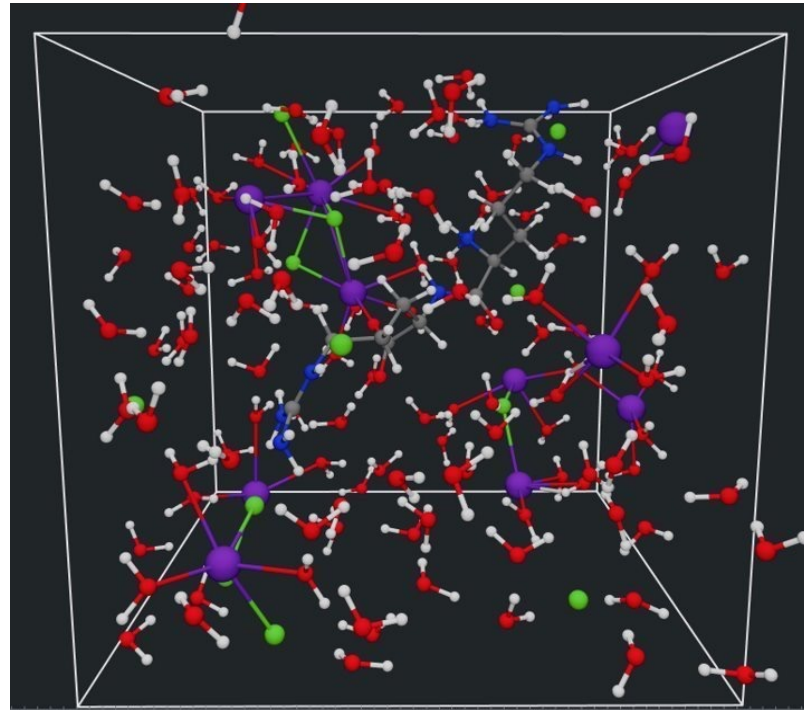
ASEGeoOpt

ASEMD

CP2K on selected snapshots

Apax check force and energy

JaxMD if runtime < 10 ns



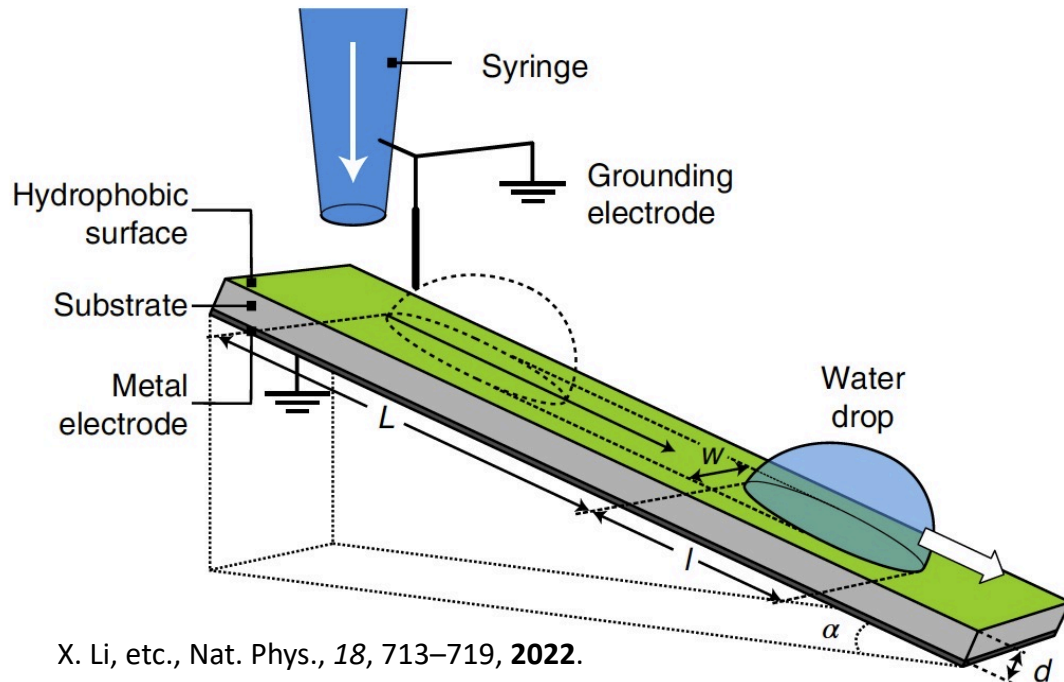
Expected goals

- Verify if MLIP-FF is reliable for peptide system in high concentration salt solution.
- Compare the peptide behavior in different salt solution, as well as in nanopore.

- Low -> high salt concentration
- Different peptide chain lengths
- Peptide condensation (box size) and structure dependance

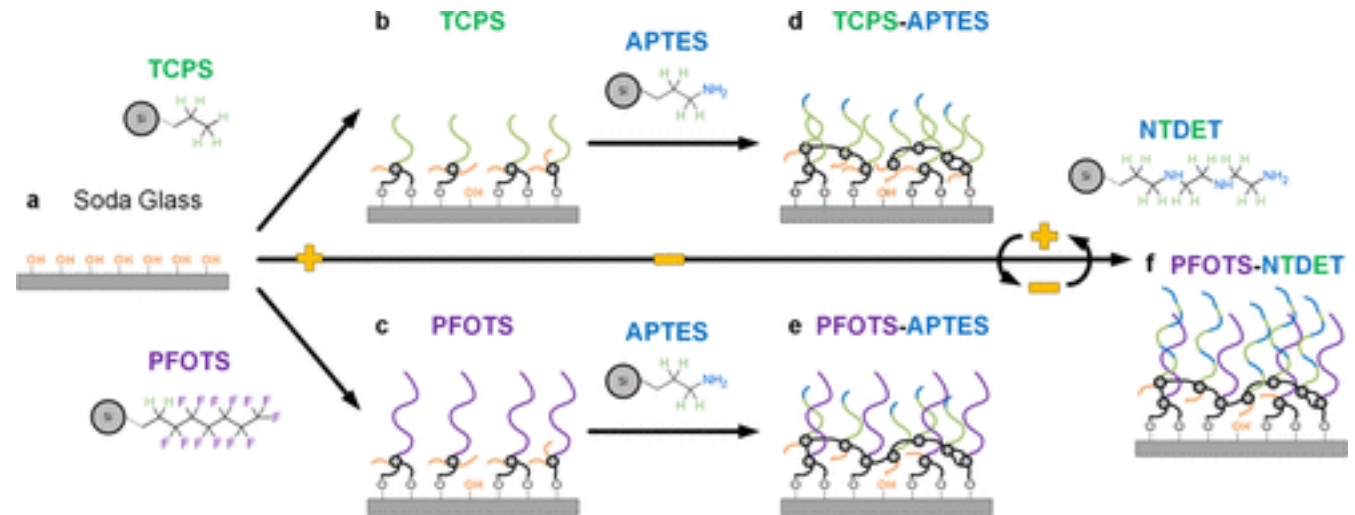
MLIP aided water decomposition dynamics on hydrophobic surfaces

Water drop-sliding exp.

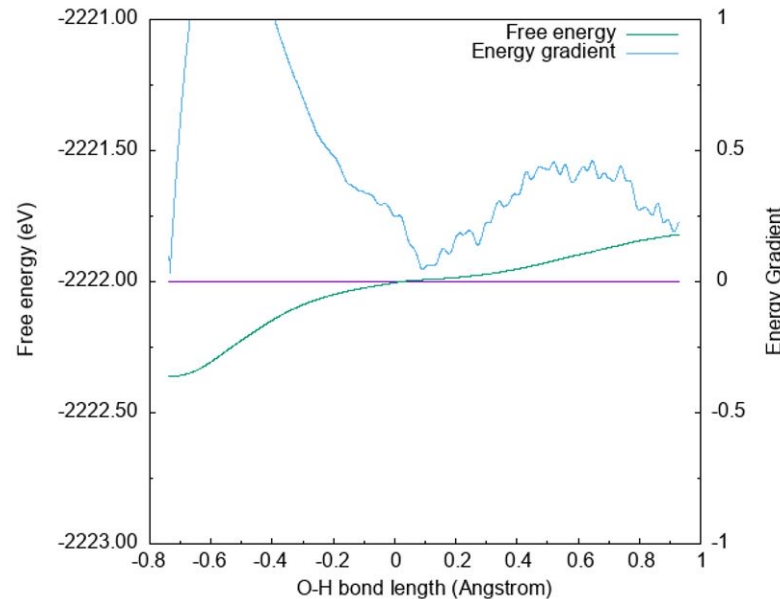
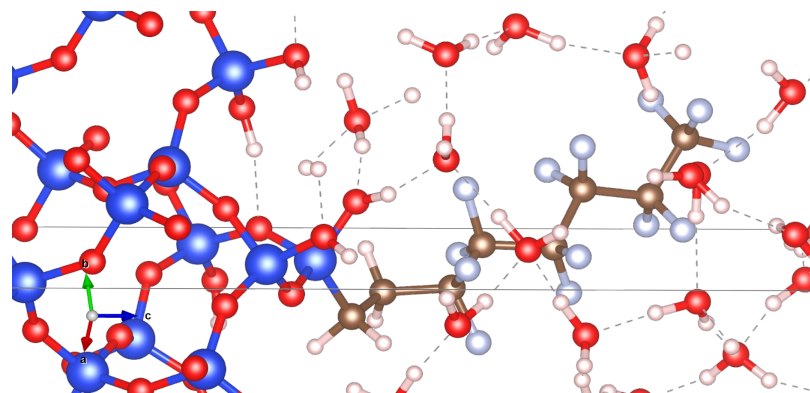
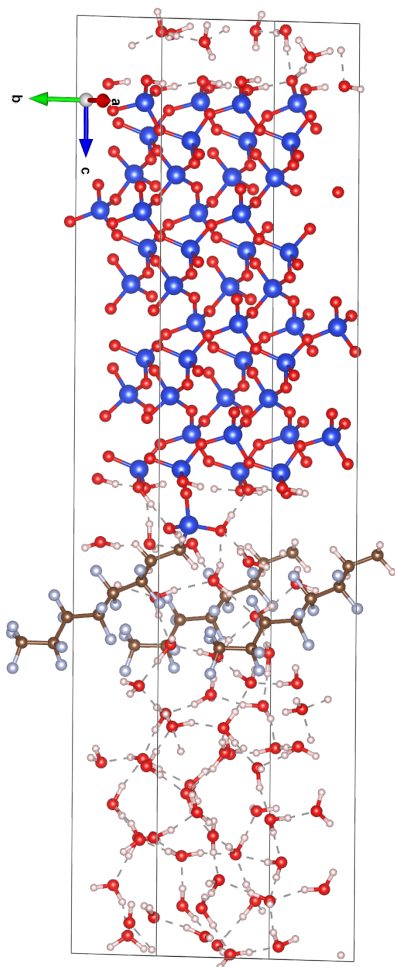


X. Li, etc., Nat. Phys., 18, 713–719, 2022.
 WSY Wong, etc., Langmuir, 38, 6224–6230, 2022.

Hydrophobic surface preparation



Dataset Design and Work Flow



Slow-growth sampling

Initial structure/box construction

ASEGeoOpt

ASEMD

CP2K on selected snapshots

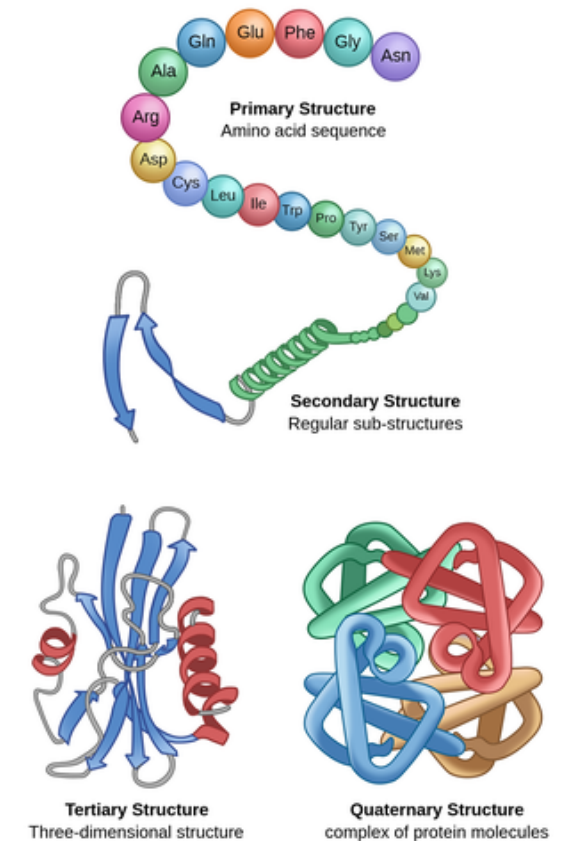
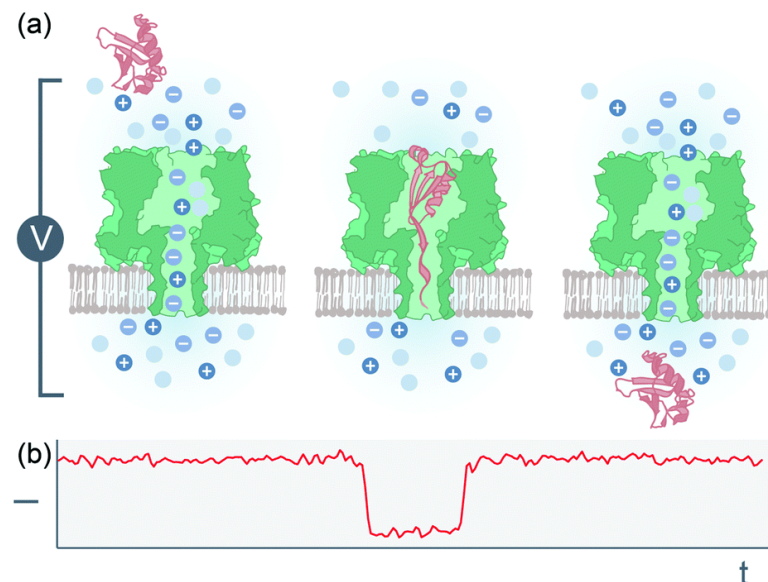
Apax check force and energy

JaxMD if runtime < 10 ns



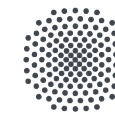
- Protein structure is determined by the amino acid sequence
- Mutations in the sequence can lead to malfunction and diseases

→ Fast & efficient detection of mutations can save lives

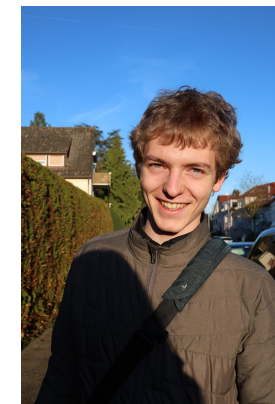
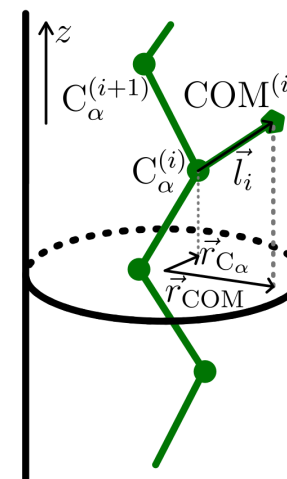
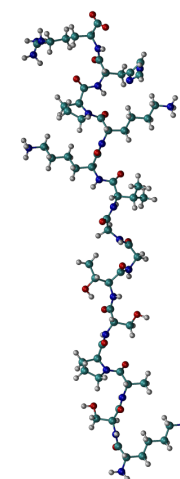


⇒ Amplitude, duration and frequency of blockade current reveal information about the protein

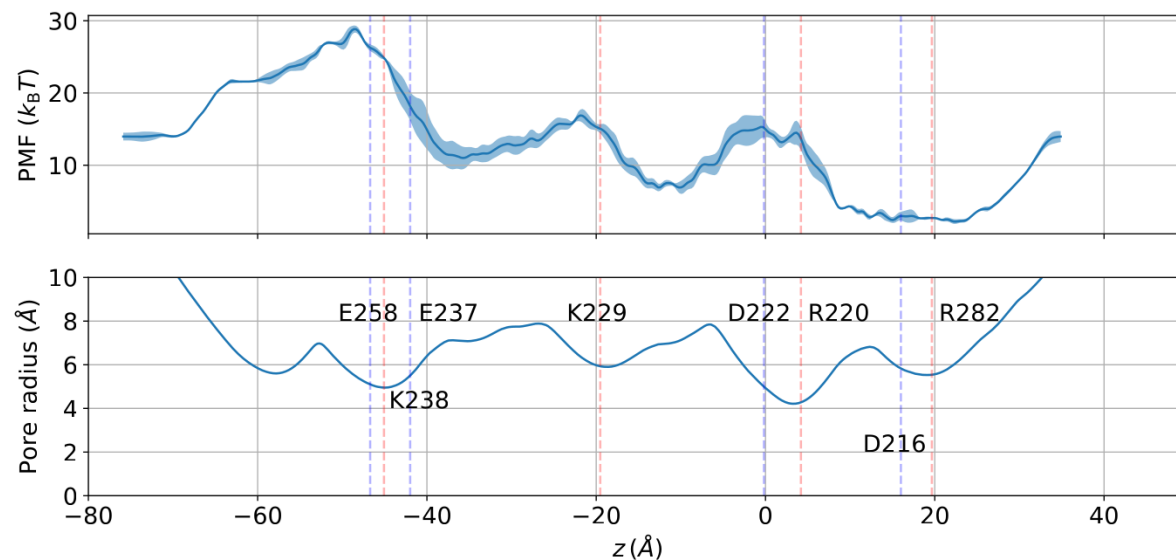
What did other students do?



- Computational Investigation of Methylated Histone Fragments for Nanopore Sensing Applications
- Investigation of Macromolecular Translocation Events Using Free-Energy Methods

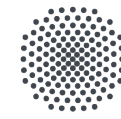


Benedikt
Veit



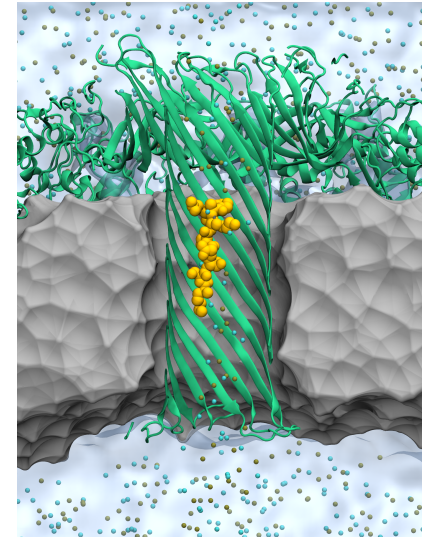
Sylvie Eckert

What will you do?



You will learn how to ...

- Perform all-atom simulations of various nanopore systems
- Apply advanced computational techniques
- Extract physics from simulation data
- Investigate the mechanism behind nanopore sensing



For more information, please contact
michel.mom@icp.uni-stuttgart.de and visit
<https://www.icp.uni-stuttgart.de/research/nanopore-sequencing/>



Single-molecule protein sensing

- What features do these events have in common?
- Can we design algorithms to recognize these features?

Bachelor's Thesis: Designing artificial signals

Problem:

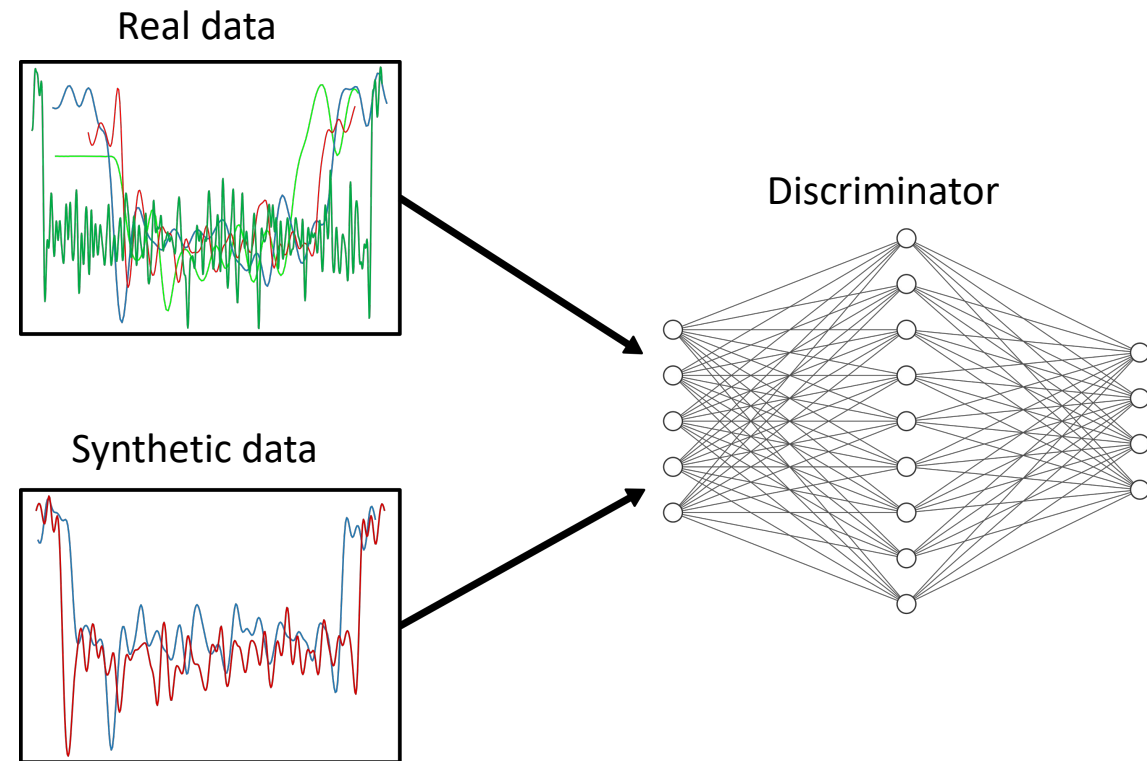
- Experimental data requires time to acquire
 - Quality of data varies between measurements
- ➔ Can we increase our dataset with artificial data?

Task:

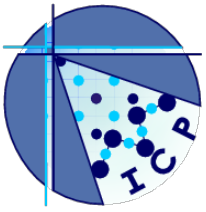
- Design methods for creating artificial events
- Evaluate artificial data on classification tasks using machine learning



Contact: Julian Hoßbach
jhossbach@icp.uni-stuttgart.de



Understanding Ion Binding in Alginate via Simulations



- Alginate network formation is controlled by monomer sequence and ion-specific interactions.
- **Objective:**
 - Benchmark and compare force fields by computing ion–alginate binding free energies.

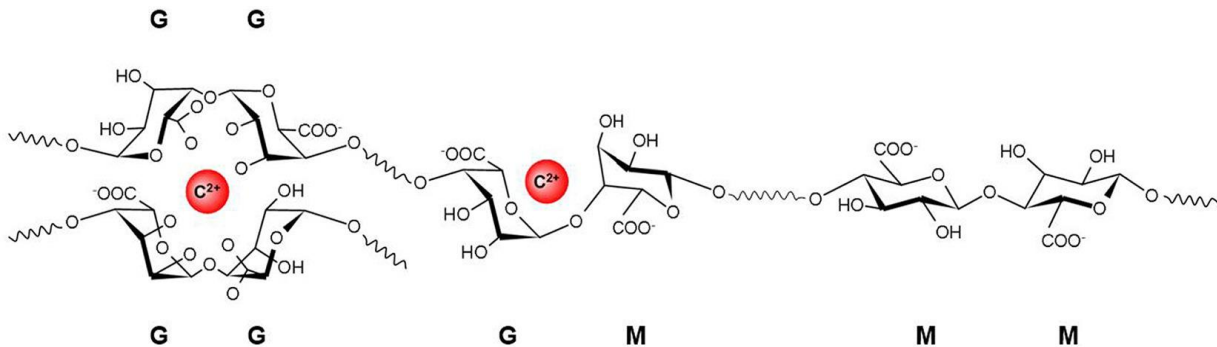


Fig. 1. Alginate molecular structure showing binding sites for divalent cations. The red circles represent cations. (C: cation; G: α -L-guluronic acid; M: β -D-mannuronic acid). DOI:[10.1016/j.ijbiomac.2021.02.086](https://doi.org/10.1016/j.ijbiomac.2021.02.086)

Tasks:

- Compute potential of mean force (**PMFs**) between alginate M/G monomers and multivalent ions (*CHARMM, GLYCAM, others*)
- Quantify **binding affinity differences across force fields**
- Assess consistency with **experimental ion selectivity**
- Use validated interactions to **parametrize coarse-grained potentials**.

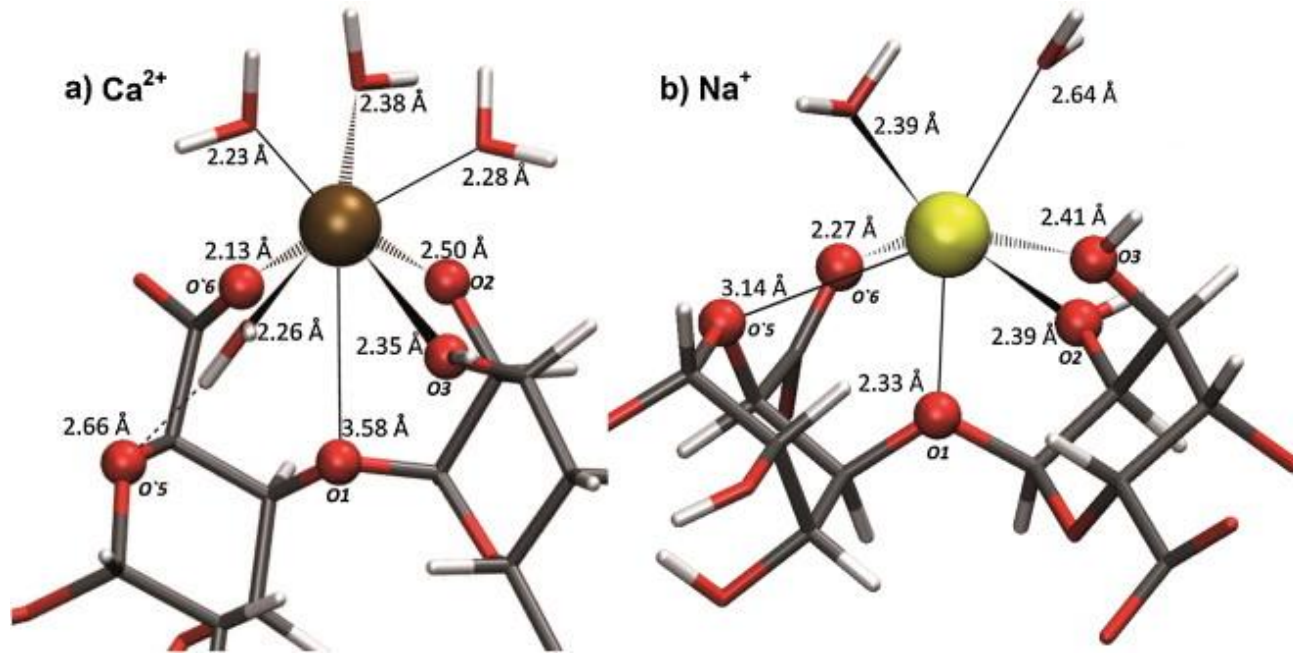
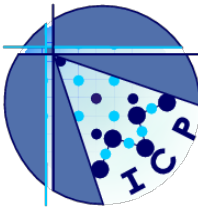


Fig. 2. Egg-box binding sites: (a) Ca^{2+} (brown) with water bridge to O'5; (b) Na^{+} (yellow). Poly-G oxygens are red; coordinated waters shown as sticks. (See web version for color references.) DOI: [10.1016/j.carbpol.2013.11.034](https://doi.org/10.1016/j.carbpol.2013.11.034)

Skills you will gain:

Molecular dynamics · Free-energy calculations · Force-field benchmarking · Coarse-grained modeling

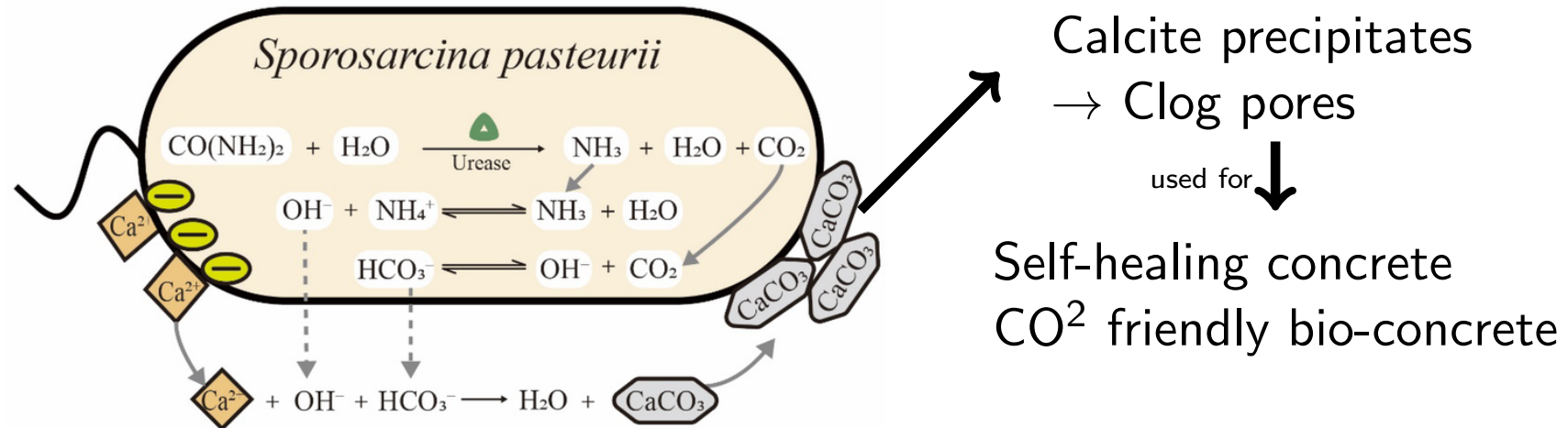
For more information, please contact hensi.gandhi@icp.uni-stuttgart.de



Outcomes:

- Identify which force fields reliably reproduce ion–alginate binding trends
- Provide validated interaction parameters for coarse-grained modeling of alginate gels

Microbial Induced Calcite Precipitation



Methods

- Reactants as densities of different species localized on a grid
- Using Finite-Volume to solve the Reaction-Diffusion-Advection PDE
- Precipitation changes the system geometry and flow behavior

Crystal growth dynamics in Nanopores

aagrawal@icp.uni-stuttgart.de

The problem:

- In porous materials, salts crystallisation affects material damage, permeability, and transport
- Experiments show salt-specific behaviour -> salt can crystallise inside pores (subflorescence) or outside as crusts (efflorescence)
- But the molecular mechanism is still unclear

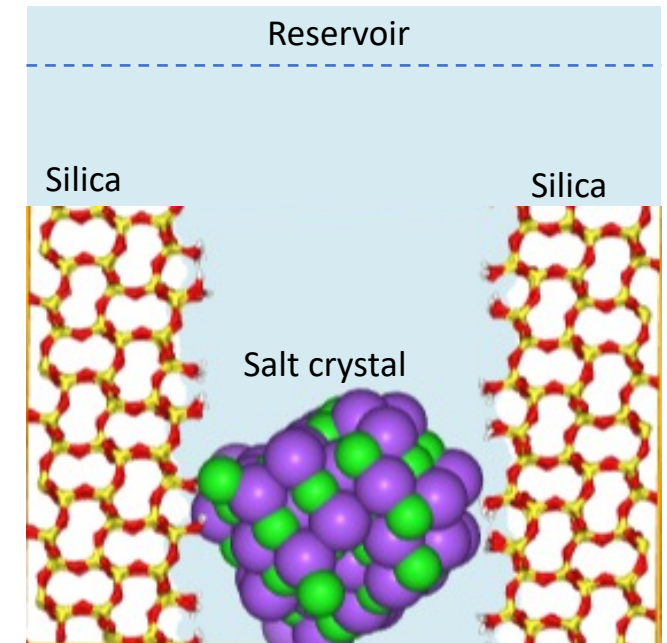
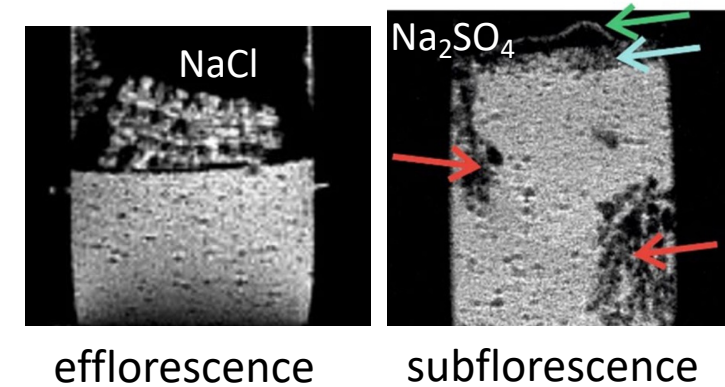
Goal: Identify **where crystallisation becomes irreversible** for different salts

Step 1: Model a **silica nanopore** in water with a salt solution

Step 2: **Control concentration** using a reservoir (constant supersaturation)

Step 3: Compare salts and **observe nucleation** and growth

- where does it start?
- how does it grow?



Machine-Learned Implicit Solvent Model for Simple Salts

- The problem:** Explicit-solvent MD of electrolytes is expensive
- Millions of water atoms
 - Small timesteps
 - Long timescales needed for nucleation/growth

Goal: Retain solvent effects on ions **without simulating water**

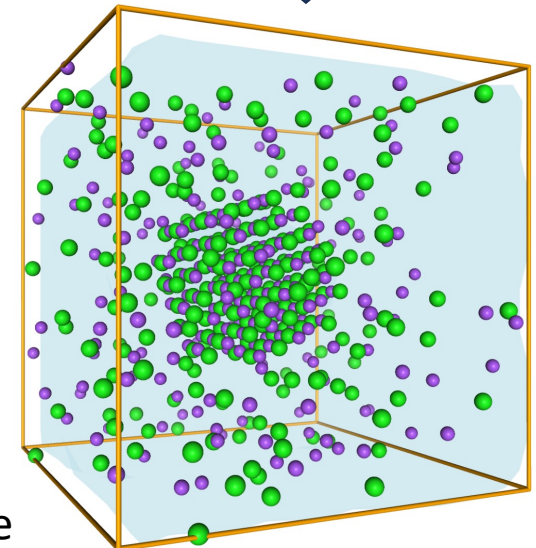
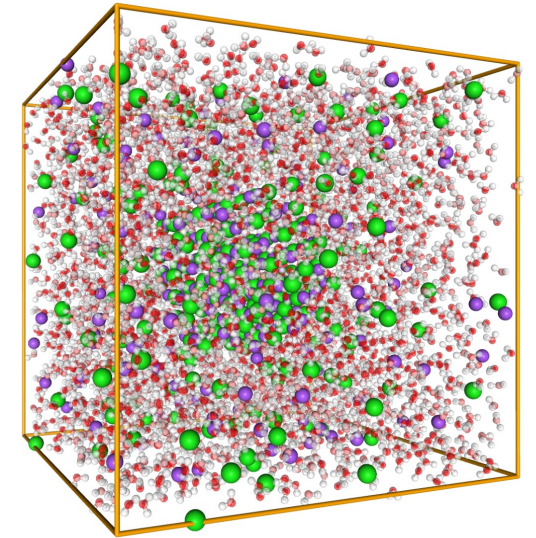
Step 1: Learn a **potential of mean force (PMF)** for ions from explicit-water MD

Step 2: Add **Langevin dynamics** with a friction γ

$$m\ddot{\mathbf{R}} = -\nabla U_{\text{PMF}}(\mathbf{R}) - \gamma\dot{\mathbf{R}} + \sqrt{2\gamma(c)k_B T} \eta(t)$$

Fit γ by matching ion diffusion from explicit MD

Bonus: Learn $\gamma(\xi(R))$ as smooth function of local environment



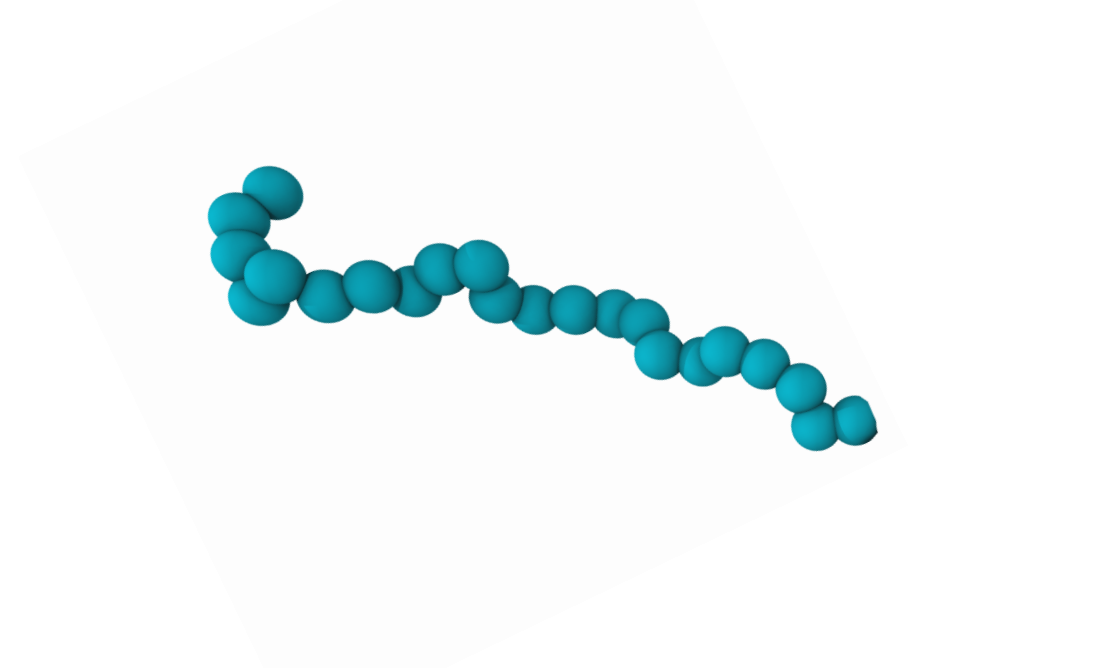
Variational Theories for Polyelectrolytes

$$\beta H_t = \frac{3}{2l} \int_0^L ds \left(\frac{d\mathbf{R}(s)}{ds} \right)^2 + l \int_0^L ds \int_0^s ds' \omega(s, s') \delta [\mathbf{R}(s) - \mathbf{R}(s')] + \frac{\lambda_B}{l^2} \int_0^L ds \int_0^s ds' q(s) q(s') \frac{\exp(-\kappa |\mathbf{R}(s) - \mathbf{R}(s')|)}{|\mathbf{R}(s) - \mathbf{R}(s')|}$$

→

$$\beta H_r = \frac{3}{2l_r} \int_0^L ds \left(\frac{d\mathbf{R}(s)}{ds} \right)^2$$

- Learn about the Edwards-Singh variational method
- Set up coarse-grained simulations of a polyelectrolyte for different chain lengths and salt concentrations
- Check the validity of variational calculations against your simulations



Contact:

David Beyer (dbeyer@icp.uni-stuttgart.de)

Lena Tarrach (lana.tarrach@icp.uni-stuttgart.de)

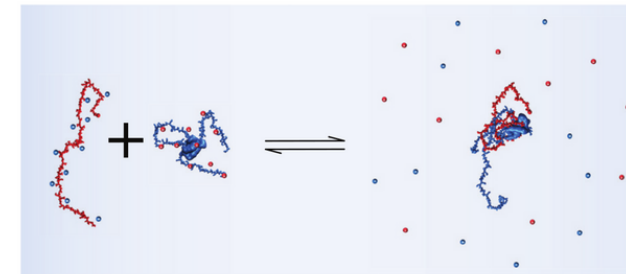
Driving Forces for Polyelectrolyte Coacervation - Enthalpy vs Entropy

- PE complex coacervate forms when oppositely charged polymers associate and phase separate.
- Discrepancy between experiments and CG simulation regarding thermodynamic driving forces on PE complex coacervation
- **Can atomistic simulation address the solvent entropy issue?**

Your Job

- Get familiar with atomistic simulation
- Calculate the PMF between ion/polyion pair
- Attribute the solvent DOF explicitly.
- Split the PMF into entropy and enthalpy contribution
- Analyze the entropy contribution further: counterion-release and electrostatic entropy

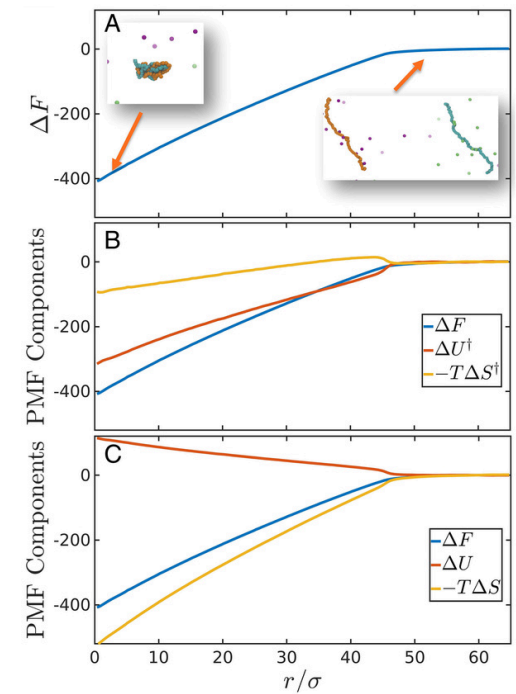
Reference: Chen et al.
<https://doi.org/10.1073/pnas.2209975119>



Methods and literature

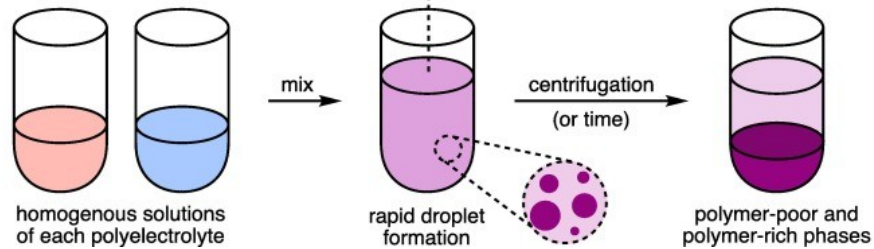
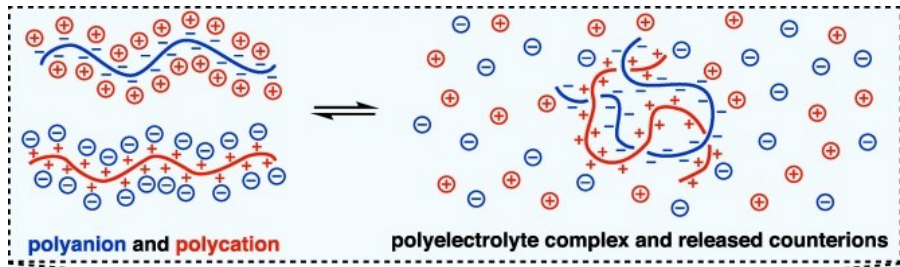
- Free energy calculation
- Familiarity with electrostatic interaction
- Statistical and thermodynamic analysis of the data
- software: Lammmps/Gromacs for atomistic simulation
- Python/C++ knowledge is advantageous

Somesh Kurahatti (somesh.kurahatti@icp.uni-stuttgart.de)
Lena Tarrach (lena.tarrach@icp.uni-stuttgart.de)
David Beyer (david.beyer@icp.uni-stuttgart.de)



How does the polymer architecture affect the hydrodynamic properties of polyelectrolyte complex coacervates?

Polyelectrolyte (PE) complex coacervation



Neitzel, De Hoe & Tirrell *Current Opinion in Solid State and Materials Science* 2021 25 (2) 10089



Spruijt, Stuart & van der Gucht *Macromolecules* 2013 46 (4), 1633-1641

Why should this be interesting to you?

- Relevance in drug delivery or cell formation

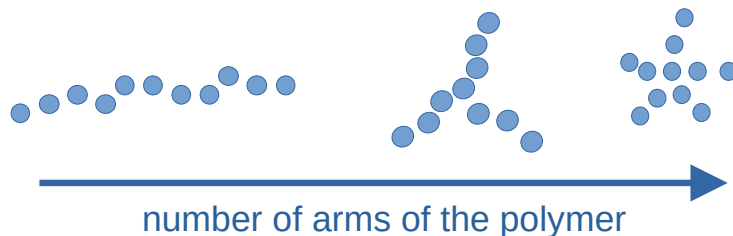
What will you do?

- Coarse-grained molecular dynamics simulation with ESPResSo
- Theoretical physics to compute properties
- Analysis of simulation data

What will you learn?

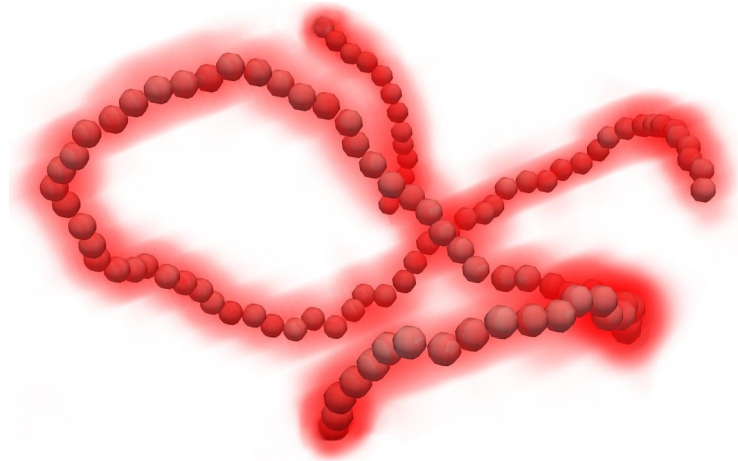
- Structure-property relations of PE complex coacervates
- Molecular dynamics simulations
- How to work on a research project

Polymer architecture



Lena Tarrach, lena.tarrach@icp.uni-stuttgart.de
David Beyer, david.beyer@icp.uni-stuttgart.de

Coupling of flexible polyelectrolytes to continuum solvent

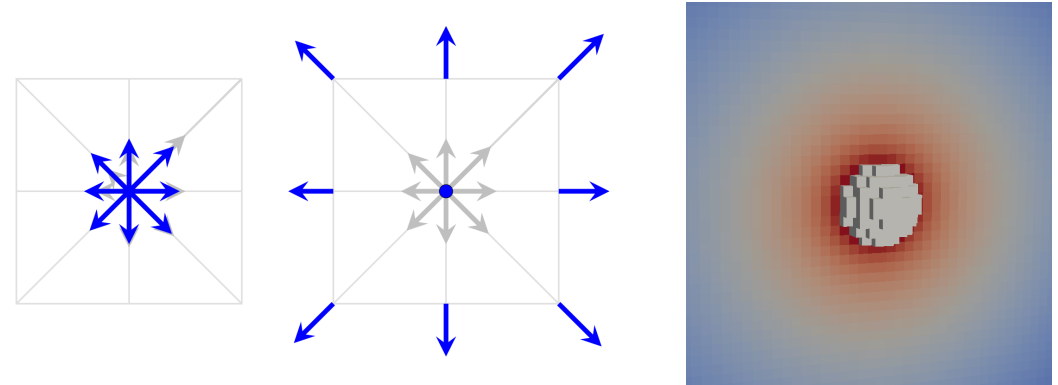


How to couple particle method for charged polymers to continuum method for ions and fluid

Your Job

- Improve existing electrostatic coupling
- Verify against Molecular Dynamics simulations
- Implement more advanced couplings if needed

Method: Lattice Boltzmann + Lattice Electrodynamics

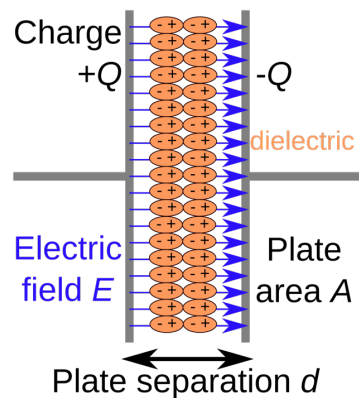


You will learn

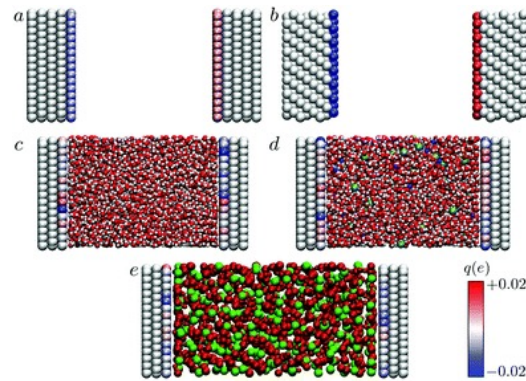
- Mesoscale lattice-based solver for hydrodynamics/Nernst-Planck equation
- Molecular Dynamics and electrostatic solvers
- Python and C++

Alexander Reinauer (alexander.reinauer@icp.uni-stuttgart.de)
Rudolf Weeber (rudolf.weeber@icp.uni-stuttgart.de)

Implement high-performance constant-potential library



Wikipedia



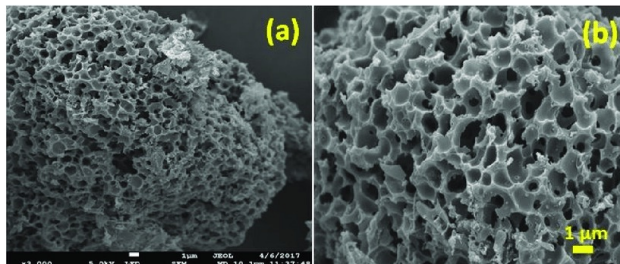
Scaffi et al. Physical Chemistry Chemical Physics 22.19 (2020): 10480-10489.

What to do?

- Implementation of existing constant potential models
- High performance development
- Usable with different MD-codes

What you will learn:

- Electrostatic Solvers
- Constant Potential algorithms
- Python
- C++



Carbon electrode, DOI: 10.1039/C9NA00374F

Alexander Reinauer (alexander.reinauer@icp.uni-stuttgart.de)
Rudolf Weeber (rudolf.weeber@icp.uni-stuttgart.de)

Accelerate charged soft matter simulations

- The Monte Carlo (MC) method can model chemical reactions and dissociation of charged groups from polyelectrolytes
- Goal: speed up simulations by calculating electrostatic energy differences more efficiently
- Requires some C++ experience

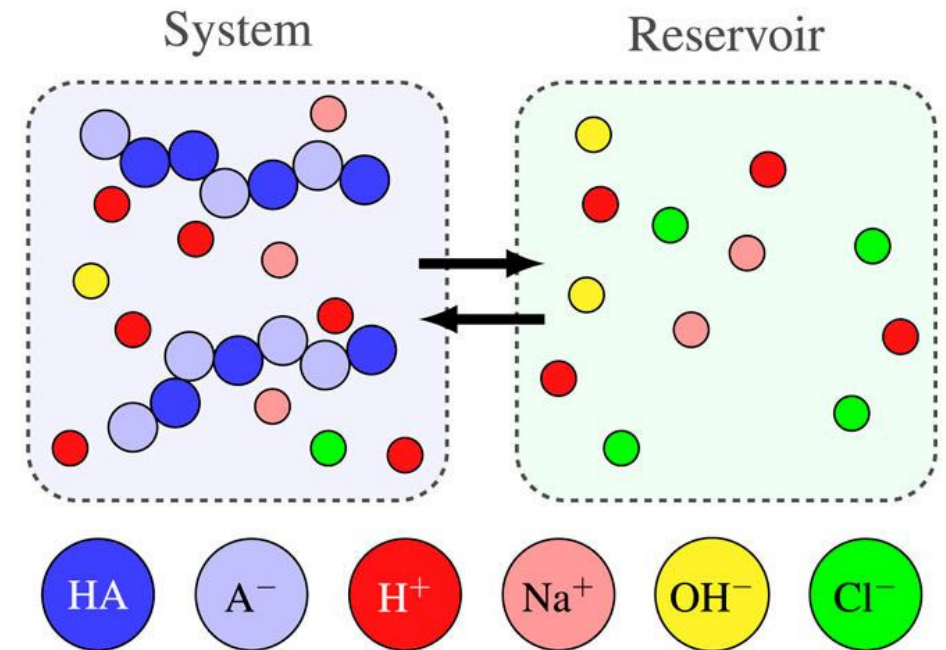


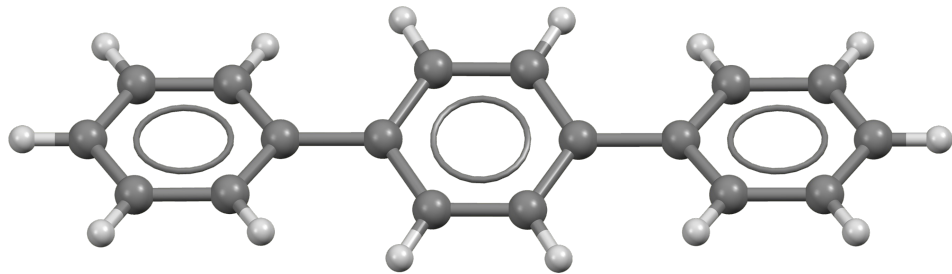
Image credit: Beyer et al. 2024, DOI:[10.1063/5.0216389](https://doi.org/10.1063/5.0216389)

Rigid-Bond Molecular Dynamics in the NPT Ensemble

NPT simulations are essential to reproduce experimental conditions (constant T,P) and ensure correct system density.

- Challenge:** Rigid bonds allow larger timesteps, but conflict arises when the barostat scales coordinates while constraints attempt to fix bond lengths.
- Solution:** A symplectic Trotter splitting (MTK equations + RESPA) resolves this by mathematically defining the correct order of scaling and constraining. **Implement this scheme into ESPResSo!**

De Michele, C., & Ciccotti, G. (2025) *Molecular Physics*, 123(3), e2364834, (2025)

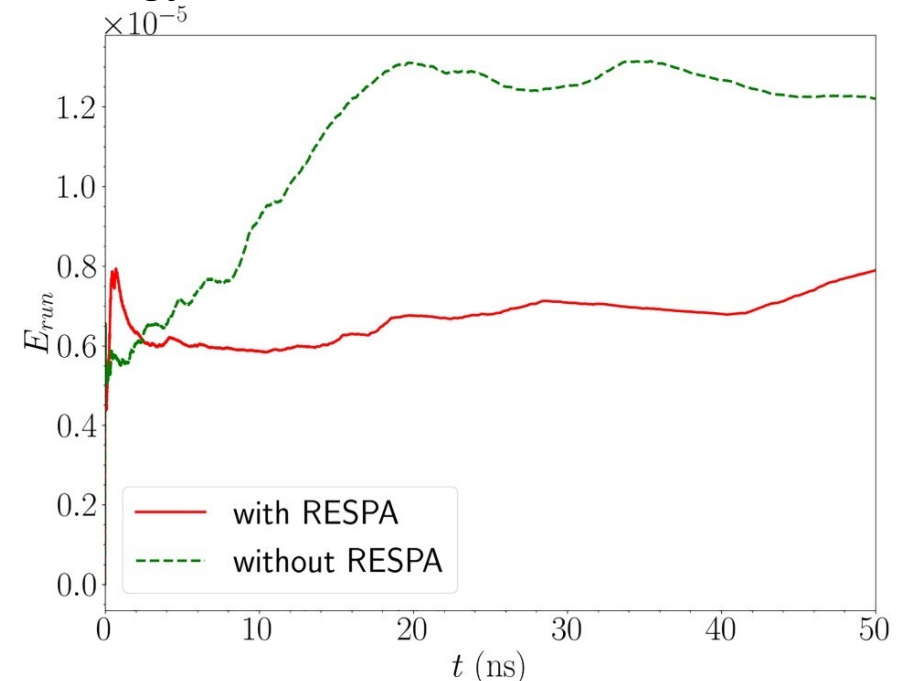


Orthotherphenyl (OTP) model

<https://en.wikipedia.org/wiki/Terphenyl>

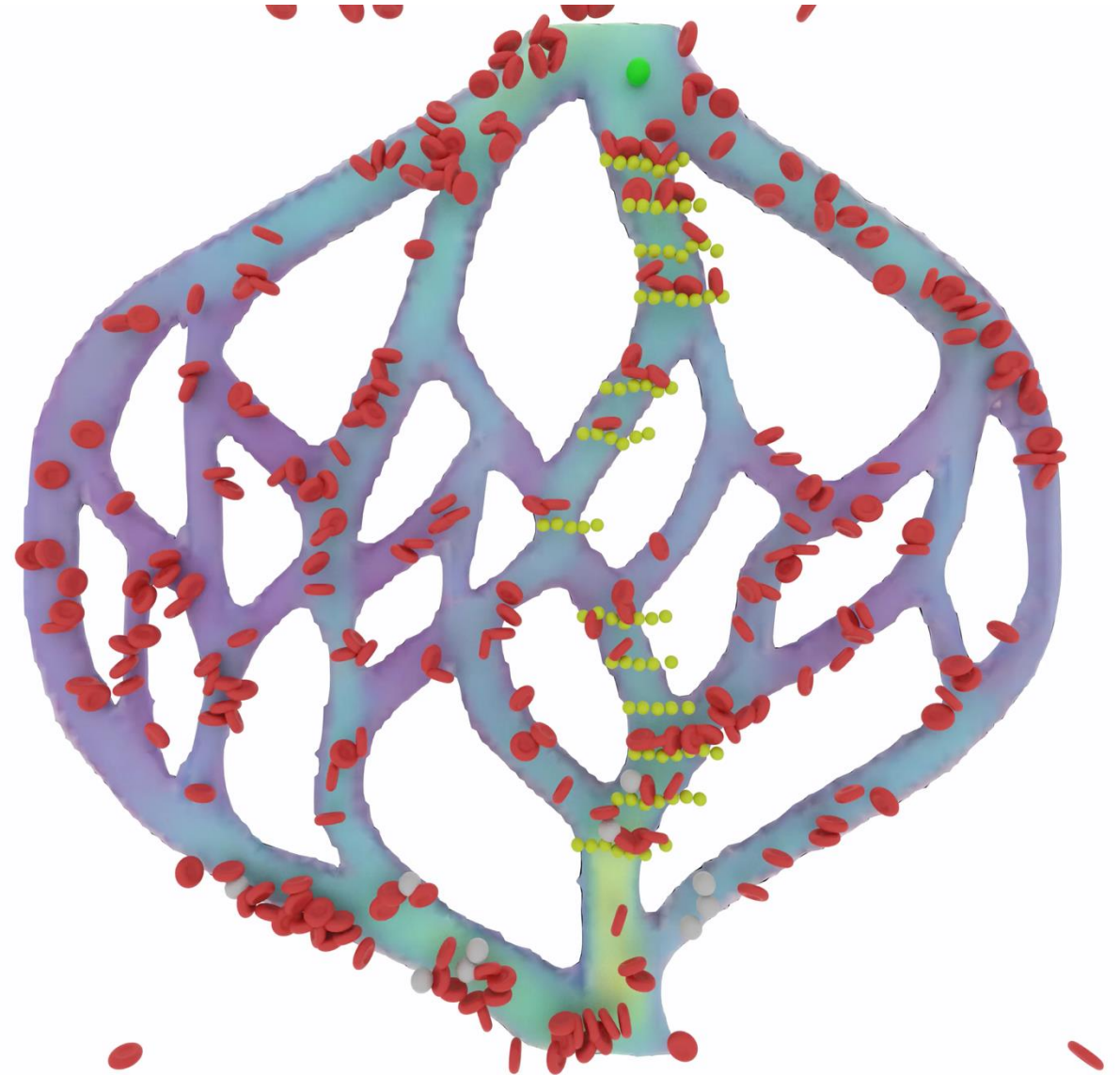
hideki.kobayashi@icp.uni-stuttgart.de

Energy conservation with OPT model in NPT



Microrobotic Control with Reinforcement Learning

- Imitation learning for microrobotic strategies
- LLM-assisted training of multi-agent simulations
- Contribute to SwarmRL software.
- Deploy models on GPU infrastructure.



The Lagrangian of Learning

$$T = \frac{1}{2} m \dot{\theta}^2$$

$$V = V(\theta)$$

$$\frac{\partial L}{\partial t} (2 \cdot \dot{\theta}^2 - \frac{\partial}{\partial t})$$

$$\pi \frac{\partial}{\partial t} + \frac{\partial V}{\partial \theta} = 0$$

- Implement Lagrangian dynamics for a neural network.
- Explore conservation laws and Hamiltonian representations.
- Explore a vast range of neural network architectures.

Lagrangian Mechanics for Neural Networks

$$L = T - V$$

$$T = \frac{1}{2} m \dot{\theta}^2 - V(\theta)$$

$$\frac{d}{dt} \left(\frac{\partial L}{\partial \dot{\theta}} \right) - \frac{\partial L}{\partial \theta} = 0$$

Quantum Reservoir Computing

How to teach quantum
systems to predict time
series?



Quantum Reservoir Computing (QRC)

Possible Topics

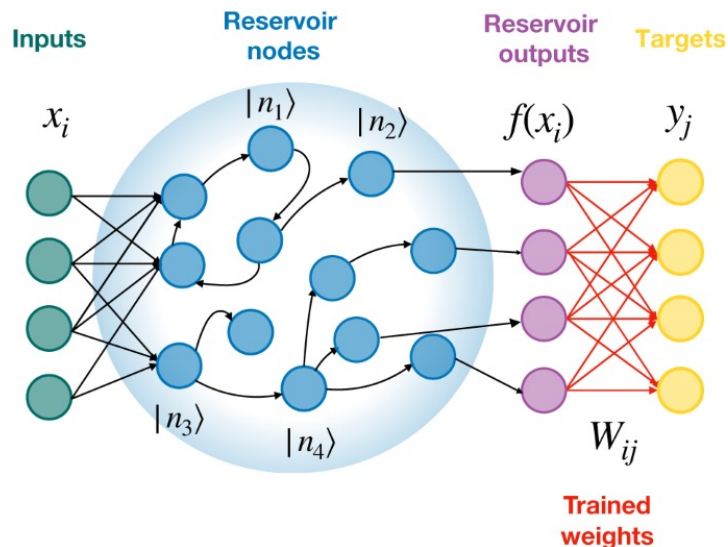
- Develop and investigate QRC with feedback
- Apply QRC to nitrogen-vacancy systems
- Study the interplay of decoherence and robustness in QRC

Requirements

- Basic understanding of quantum physics
- Good knowledge in Python

What you can learn

- Simulating quantum physical systems
- Insights into quantum computing and quantum machine learning



doi.org/10.1038/s41534-023-00734-4



tobias.fellner@icp.uni-stuttgart.de

Bachelor, Masters or PhD topics



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For more informations visit the ICP website

www.icp.uni-stuttgart.de



For Teaching overview: See <https://www2.icp.uni-stuttgart.de/~icp/Teaching/Overview>

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- Lena Tarrach lena.tarrach@icp.uni-stuttgart.de
- Samuel Tovey stovey@icp.uni-stuttgart.de

Machine learned potentials

ML for Physics

2-Phase LB, electrokinetic algorithms

Nanopore and all atom simulations

Weak polyelectrolytes,

atomistic MD simulations of salt crystallization in porous media

Quantum Computing algorithms, QML

Supercapacitors

ESPResSo, Lattice-Boltzmann

ESPResSo Software

ESPResSo, Magnetic Soft Matter, Polymer Rheology

Machine learning for Signal processing, nanopore currents

Magnetic Gels, Viscosity simulations with LB

Models for alginates and pectins

Coacervates and weak polyelectrolytes

Machine learning in Physics