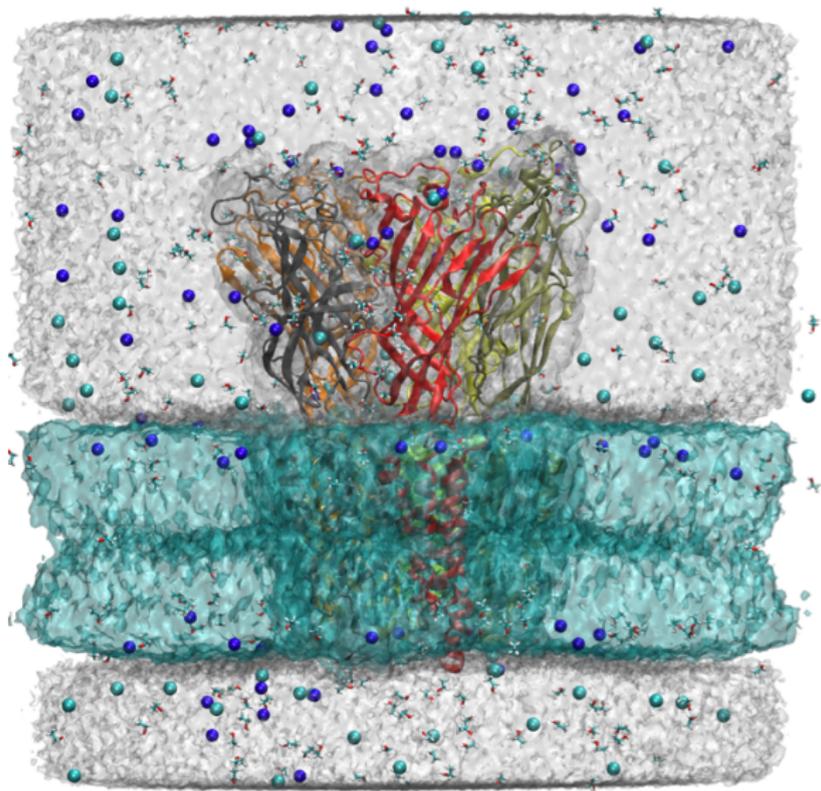


# Replica exchange molecular dynamics

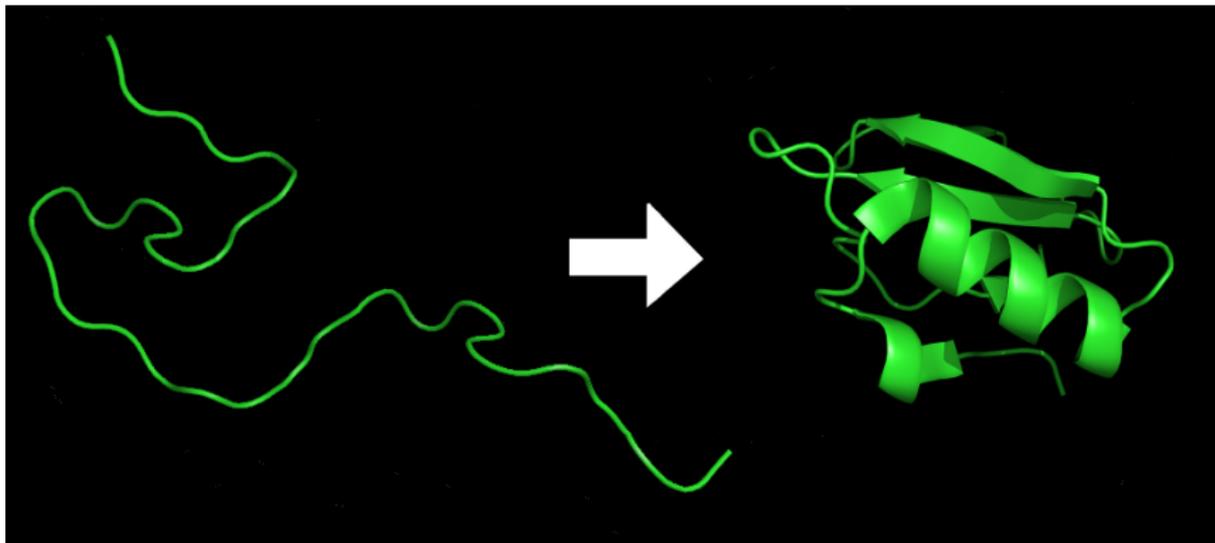
Advanced molecular dynamics course, KTH

Dr Mark Abraham (mjab@kth.se)

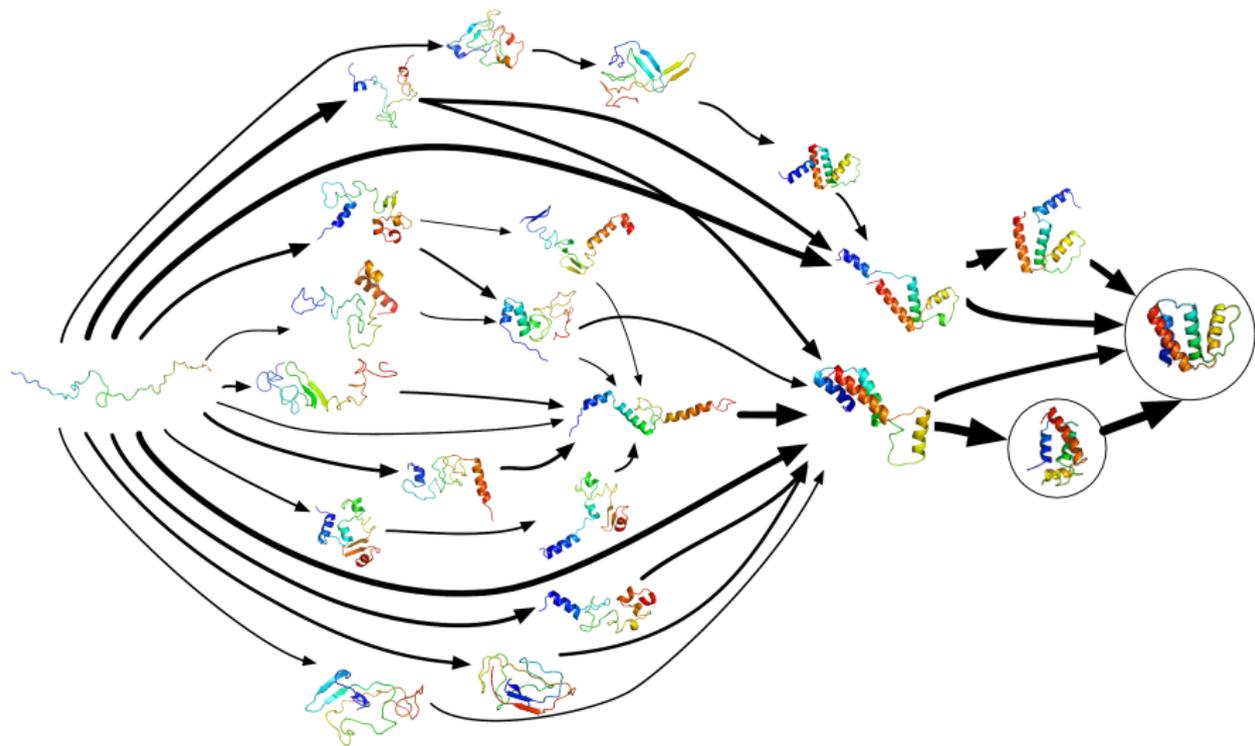
# Ion channels



# Protein folding

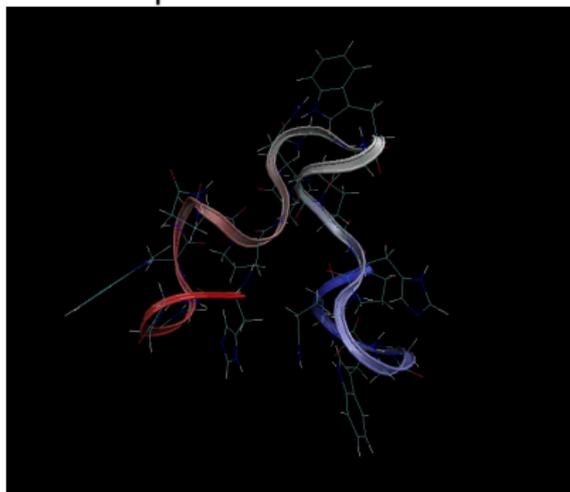


# Markov state models

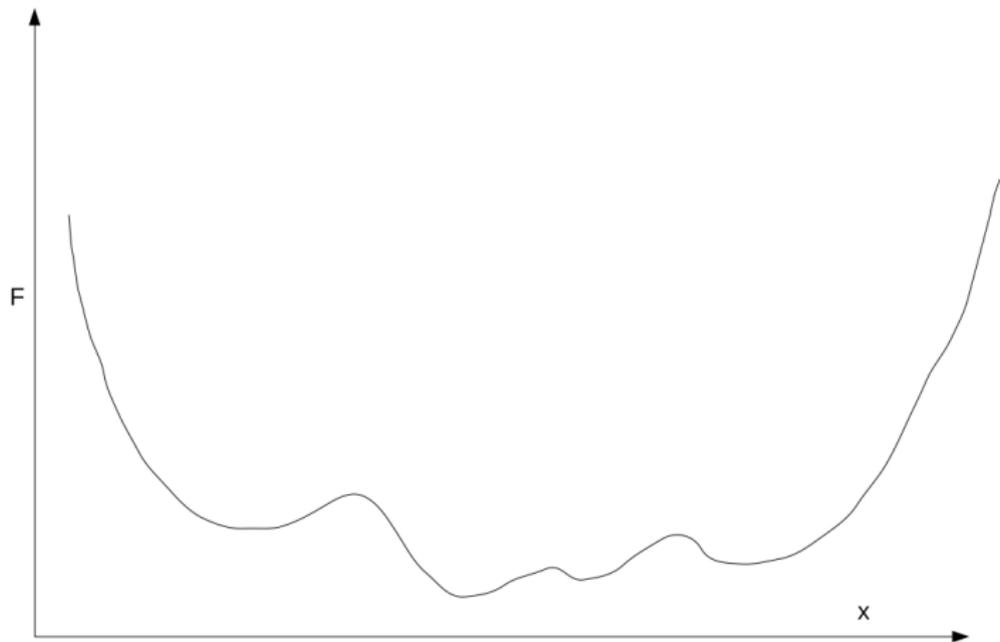


# Sampling is often frustrated

- ▶ many different motions (bonds, angles, side chains, secondary structure deformation)
- ▶ different motions have different time scales
- ▶ difficult to parameterize a model that gets it all right
- ▶ more difficult to sample from it afterwards

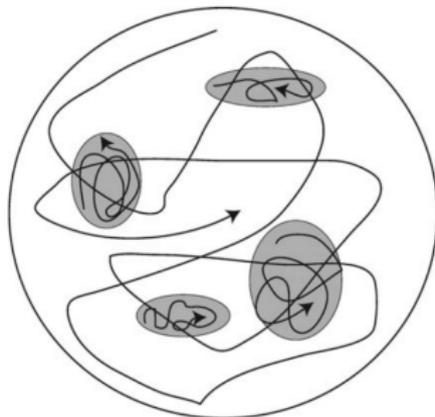


# Barriers in MD



# Frustration from barriers

- ▶ barriers of more than a few  $kT$  exist, and are hard to cross
- ▶ need extremely large amount of brute-force sampling to get over them
- ▶ makes solving problems like protein folding exceedingly computationally expensive



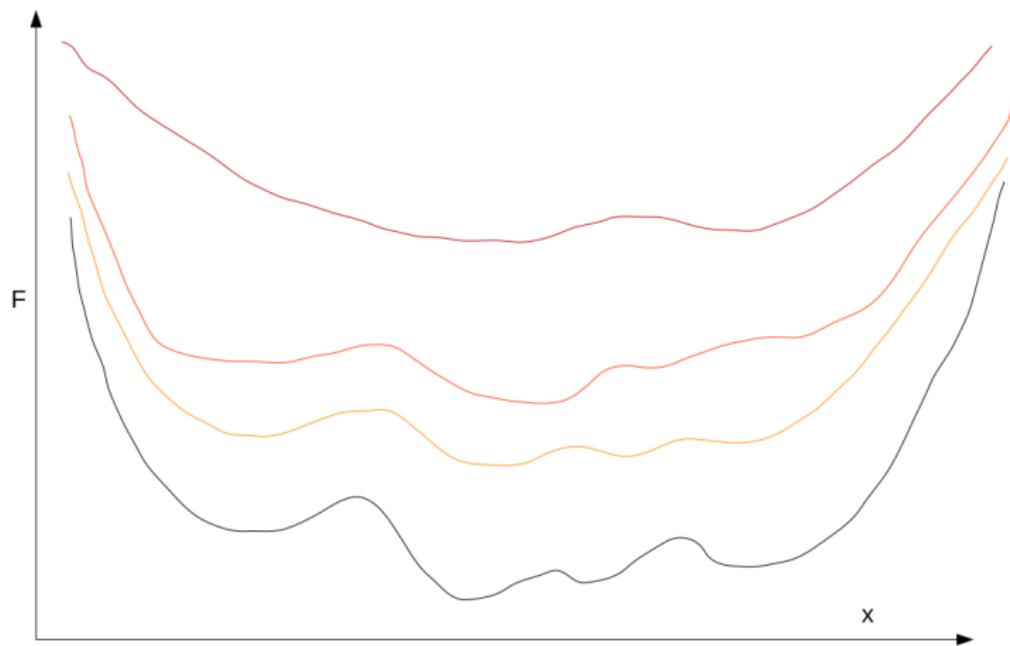
# Ways to grapple with the problem

- ▶ give up on the fine detail, and use a coarse-graining approach (next Tuesday's topic)
- ▶ accelerate the sampling (work smarter! Today's topic)
- ▶ throw more hardware at it (e.g. Folding@Home)
- ▶ write faster software (hard, very hard; also next Tuesday's topic)

# Accelerating the sampling

- ▶ if the problem is that  $kT$  is too small...
  1. increase  $T$
  2. sample widely
  3. ...
  4. profit!
- ▶ unless the landscape changes... (gulp)

## Landscapes change with temperature



# Simulated tempering

- ▶ a Monte Carlo approach to permit system to move in the space of a “control parameter”
- ▶ typically that is temperature
- ▶ only collect data when the system returns to the parameter value of interest
- ▶ this is correct if the (Metropolis) exchange criterion is correctly constructed

For a state  $s$ ,

$$P((\beta, s) \rightarrow (\beta', s)) = \min\left(1, \frac{w(\beta', s)}{w(\beta, s)}\right)$$

where  $\beta = \frac{1}{kT}$  and  $w(\beta, s) = \exp[-\beta U(s) + g(\beta)]$

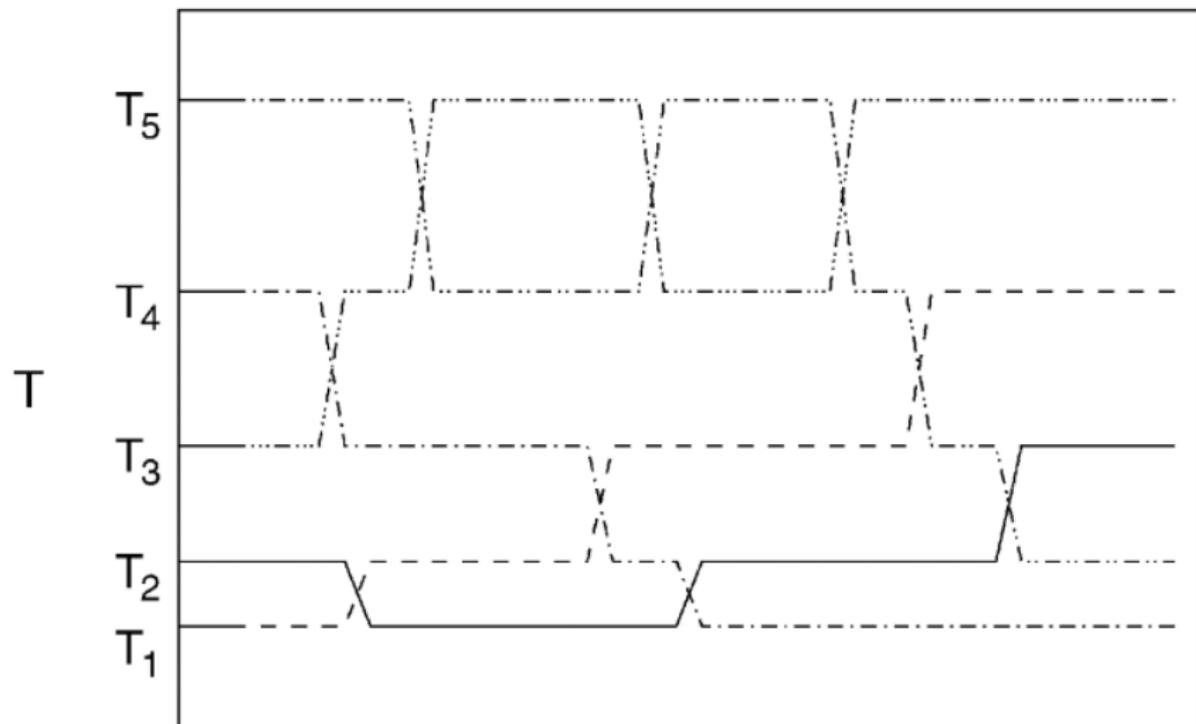
## Simulated tempering (2)

- ▶ correct if the exchange criterion is constructed correctly
  - ▶ the optimal  $g(\beta)$  is the free energy. . .
  - ▶ so you're good if you already know the relative likelihood of each conformation at each temperature. . .
- ▶ works great if you already know the answer to a harder problem than the original
- ▶ (but you can use an iterative scheme to converge on the answer)

## Parallel tempering (a.k.a. replica exchange)

- ▶ side-steps the prior-knowledge problem by running an independent copy of the simulation at each control parameter
- ▶ (note, throwing more hardware at the problem!)
- ▶ now the exchange is between copies at different control parameters, each of which is known to be sampled from a correct ensemble already
- ▶ this eliminates  $g(\beta)$  from the generalized exchange criterion...

# Parallel tempering



## Rescaling the momenta

- ▶ when proposing an exchange, can do anything to any coordinate
- ▶ accept exchange only when detailed balance is preserved
- ▶ it is convenient for the average KE after exchanges to be consistent with the target ensemble
- ▶ so rescale the momenta as

$$p_i^{\text{new}} = \sqrt{\frac{T^{\text{old}}}{T^{\text{new}}}} p_i^{\text{old}}$$

## Parallel tempering - the exchange criterion

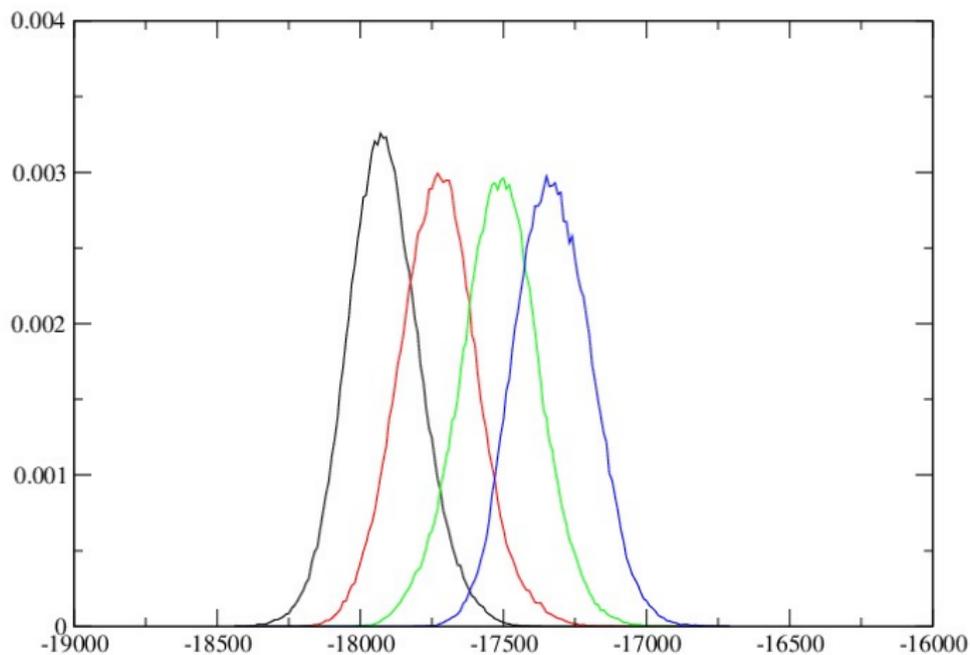
$$P((\beta, s) \leftrightarrow (\beta', s')) = \min\left(1, \frac{w(\beta, s')w(\beta', s)}{w(\beta, s)w(\beta', s')}\right)$$

For Boltzmann weights, this reduces to

$$P((\beta, s) \leftrightarrow (\beta', s')) = \min(1, \exp[(\beta' - \beta)(U(s') - U(s))])$$

# Parallel tempering - understanding the exchanges

Distribution

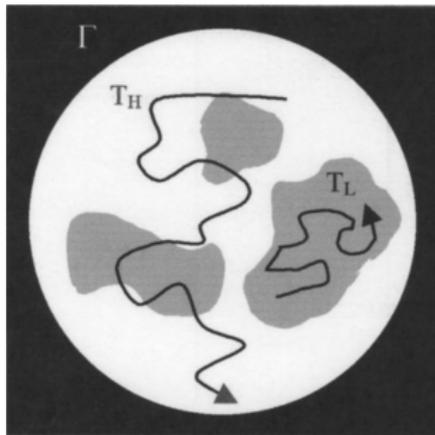


## Is this real?

- ▶ recall that  $P(\beta, s) \propto \exp[-\beta U(s)]$
- ▶ any scheme that satisfies detailed balance forms a Markov chain whose stationary distribution is the target (generalized) ensemble
- ▶ so we require only that
$$P(\beta, s)P((\beta, s) \rightarrow (\beta', s)) = P(\beta', s')P((\beta', s') \rightarrow (\beta, s))$$
- ▶ which is what was constructed!
- ▶ However, dynamical information is lost when exchanges happen

## Might this work?

- ▶ high-temperature replicas hopefully can cross barriers
- ▶ if the conformations they sample are representative of lower-temperature behaviour, then they will be able to exchange down
- ▶ if not, they won't



## Ensembles commonly used

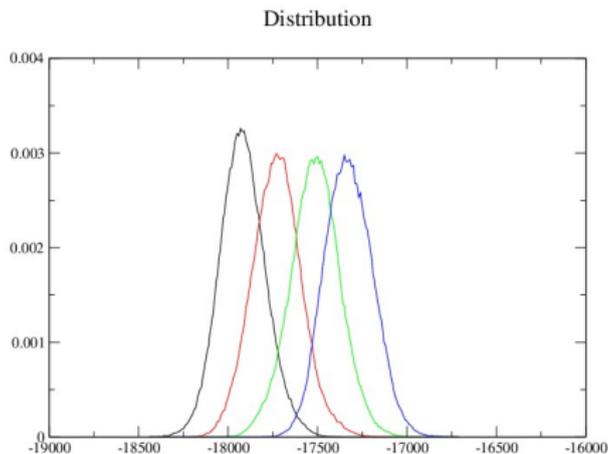
- ▶ natural to use the NVT ensemble with an increasing range of  $T$  and constant  $V$
- ▶ remember that we must rescale the velocities to suit the new ensemble in order to construct the above exchange criterion
- ▶ probably this should use a velocity-Verlet integrator ( $x$  and  $v$  at same time)
- ▶ in principle, can use other ensembles like NPT

## Ensembles commonly used

- ▶ NVT at constant volume must increase  $P$  with  $T$
- ▶ that seems unphysical
- ▶ worse, the force fields are parameterized for a fixed temperature
- ▶ but the method doesn't require that the ensembles correspond to physical ones
- ▶ merely need overlap of energy distribution
- ▶ the size of the overlap determines the probability of accepting an exchange

# Problems with replica exchange

- ▶ molecular simulations typically need lots of water
- ▶ thus lots of degrees of freedom
- ▶ energy of the system grows linearly with system size
- ▶ width of energy distributions grow as  $\sqrt{\text{size}}$
- ▶ need either more replicas or accept lower overlap



# Unphysics is liberating

- ▶ if there's no need to be physical, then may as well be explicit about it
- ▶ large number of proposed schemes

Example: resolution exchange

- ▶ run replicas at different scales of coarse graining
- ▶ at exchange attempts, not only rescale velocities, but reconstruct the coordinates at higher/lower grain level

# Hamiltonian replica exchange

- ▶  $T$  isn't the only possible control parameter
- ▶ could gradually turn on a restraint or biasing potential
- ▶ control parameters can be multi-dimensional, e.g. in a free-energy calculation, could change both alchemical transformation parameter  $\lambda$  and  $T$

# Replica exchange with solute tempering (REST)

- ▶ selectively “heat” only a small region of the system
- ▶ modify the parameters to scale the energy, rather than heating (recall that  $P(\beta, s) \propto \exp[-\beta U(s)]$ )
- ▶ advantage that the energy distribution of only part of the system increases over control parameter space
- ▶ needs many fewer replicas for given control parameter space
- ▶ implemented in many MD packages, including GROMACS, by PLUMED plugin (<https://www.plumed.org/>)

# Choices in molecular dynamics studies

- ▶ Solvation model
- ▶ Resolution of model physics
- ▶ Force field
- ▶ Statistical ensemble to sample
- ▶ Starting condition(s)
- ▶ Simulation time step
- ▶ Observables
- ▶ Data collection rate

## Additional choices in replica exchange studies

- ▶ Which control parameter? ( $T$ ,  $\lambda$ )
- ▶ At which control parameters to collect data
- ▶ Range of control parameter space
- ▶ Number of replicas
- ▶ Spacing of replicas
- ▶ Exchange probability
- ▶ Exchange attempt interval

Shameless plug: <https://dx.doi.org/10.1021/ct800016r>

# Average Exchange probability

Recall

$$P((\beta, s) \leftrightarrow (\beta', s')) = \min(1, \exp[(\beta' - \beta)(U(s') - U(s))])$$

So

$$P_{\text{ave}}((\beta, s) \leftrightarrow (\beta', s')) = \int \int \min(1, \exp[(\beta' - \beta)(U_1(s') - U_2(s))]) dU_1 dU_2$$

Generally, you want replicas whose temperatures increase roughly exponentially

# Web server for helping choose T for REMD

<http://folding.bmc.uu.se/remd-temperature-generator/>

Based on <https://dx.doi.org/10.1039/B716554D>

## Interval between exchange attempts

- ▶ Ideally, after MD step, attempt exchange
- ▶ Doesn't really matter if the exchange probability is low, you'll get some exchanges eventually
- ▶ Does this spamming help?

## Interval between exchange attempts

- ▶ observables like potential energy have autocorrelation times
- ▶ for e.g. protein in water, it's about 1 ps
- ▶ if you exchange more frequently than that, you get back exchanges <https://dx.doi.org/10.1063/1.2404954>
- ▶ so either estimate or measure the autocorrelation time, and exchange about that often

# Practical replica exchange in GROMACS

- ▶ uses the multi-simulation feature which requires building with an MPI library
- ▶ need enough resources for each simulation on its own
- ▶ put each simulation in a unique directory, using the multidir feature
- ▶ equilibrate there
- ▶ choose the number of simulation steps between exchange attempts on the command line
- ▶ use the most recent versions of GROMACS for minimal communication between simulations

# De-multiplexing

- ▶ some MD packages write a continuous trajectory of each simulation system
- ▶ others (including GROMACS) write a continuous ensemble
- ▶ demux.pl script in the GROMACS installation will convert the trajectory files between the two, based on the exchange information in the log file

# Questions?

# Tutorial

Run the online Jupyter notebook via a binder at <https://mybinder.org/v2/gl/gromacs%2Fonline-tutorials%2Fsimple-remd/main> or the “Default binder” link from <https://gitlab.com/gromacs/online-tutorials/simple-remd/-/tree/main>.

<https://gitlab.com/gromacs/online-tutorials/simple-remd/-/tree/main>.

You can access the git repository containing the materials via

```
git clone https://gitlab.com/gromacs/online-tutorials
```

Or download as a zip archive from

<https://gitlab.com/gromacs/online-tutorials/simple-remd/-/archive/main/simple-remd-main.zip>.

## Optional

Build MPI-enabled GROMACS. Get e.g. openmpi or mpich2 packages for your distro. Then configure GROMACS as normal, but add the following flag to the CMake line:

```
cmake -DGMX_MPI=on
```