

## INTRODUCTION

A **central challenge** in **molecular dynamics (MD)** simulations is the prediction of **kinetic rates**, due to the gap between the time scales accessible with MD and those of **rare events**<sup>1</sup>. Methods aiming to estimate kinetics from **enhanced sampling** techniques such as metadynamics<sup>2,3</sup>, require intensive **computer effort** and/or rely on ideal **collective variables (CVs)**. We developed an efficient methodology for the prediction of rates from time-dependent biased simulations. This strategy only require sets of **short simulations** as input data. Additionally, it allows to **assess the quality of CVs in post-processing**, avoiding the need of new expensive MD simulations.

## OUR GOALS

**1**  
Metadynamics<sup>2</sup> trajectories and **Kramers' theory** to estimate transition rates and assess the **CV quality**.

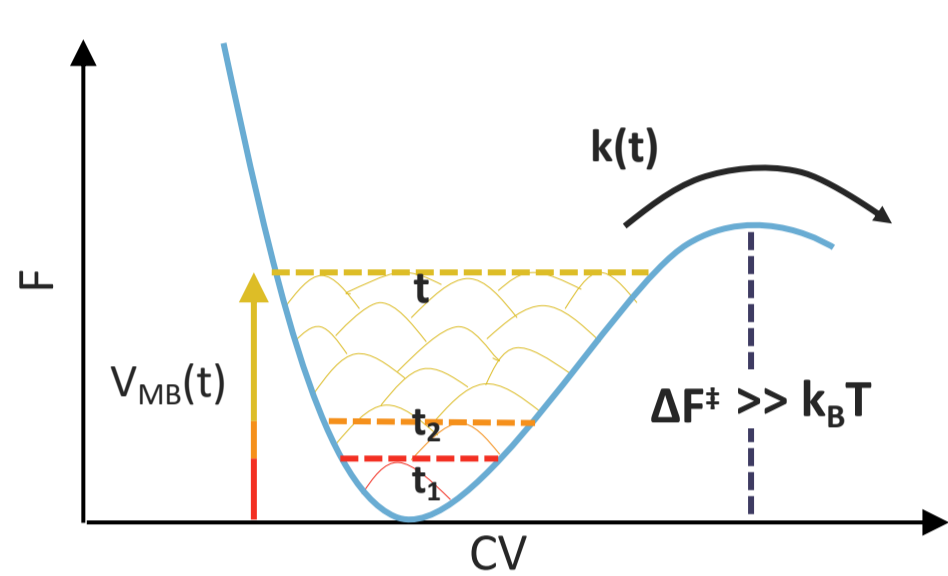
**2**  
Barrier-crossing statistics in **post-processing** with **reliability tests** at **high computational efficiency**.

## METHODS AND THEORY

**Kramers' theory** and **likelihood maximization** allow to estimate **kinetic rates** and measure the **CV quality** from single-transition **metadynamics** trajectories.

### Metadynamics (MetaD)

The barrier decreases with increasing bias, thus the **effective rate  $k(t)$**  increases with time.



### Kramers' time-dependent rate (KTR)

**True barrier** and **maximum bias**

$$k(t) = k_{pre} e^{-\beta \Delta F^\ddagger + \beta \gamma V_{MB}(t)}$$

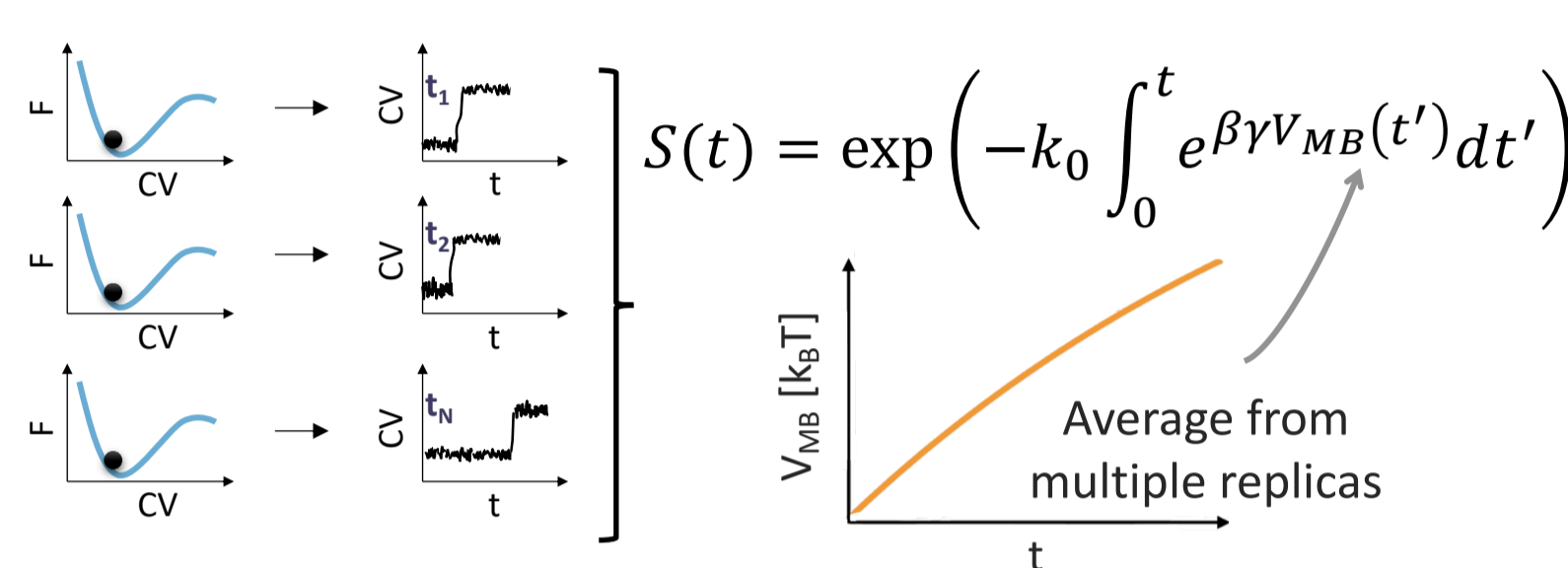
**Measure of the CV quality:**  $\gamma \in [0,1]$

$$k(t) = k_0 e^{\beta \gamma V_{MB}(t)}$$

Parameters to optimize

### Survival probability $S(t)$ <sup>4</sup>

Escape from a single free energy well.



N parallel replicas biased with metadynamics.

### Likelihood function

$$\mathcal{L} = \prod_{i \in \text{events}}^M -\frac{dS(t)}{dt} \Big|_{t=t_i} \prod_{j \in \text{non-events}}^{N-M} S(t_j)$$

Extract  $\gamma$  and  $k_0$  that maximize the likelihood. Perform KS-tests with the empirical and predicted CDFs<sup>5</sup>.

## RESULTS

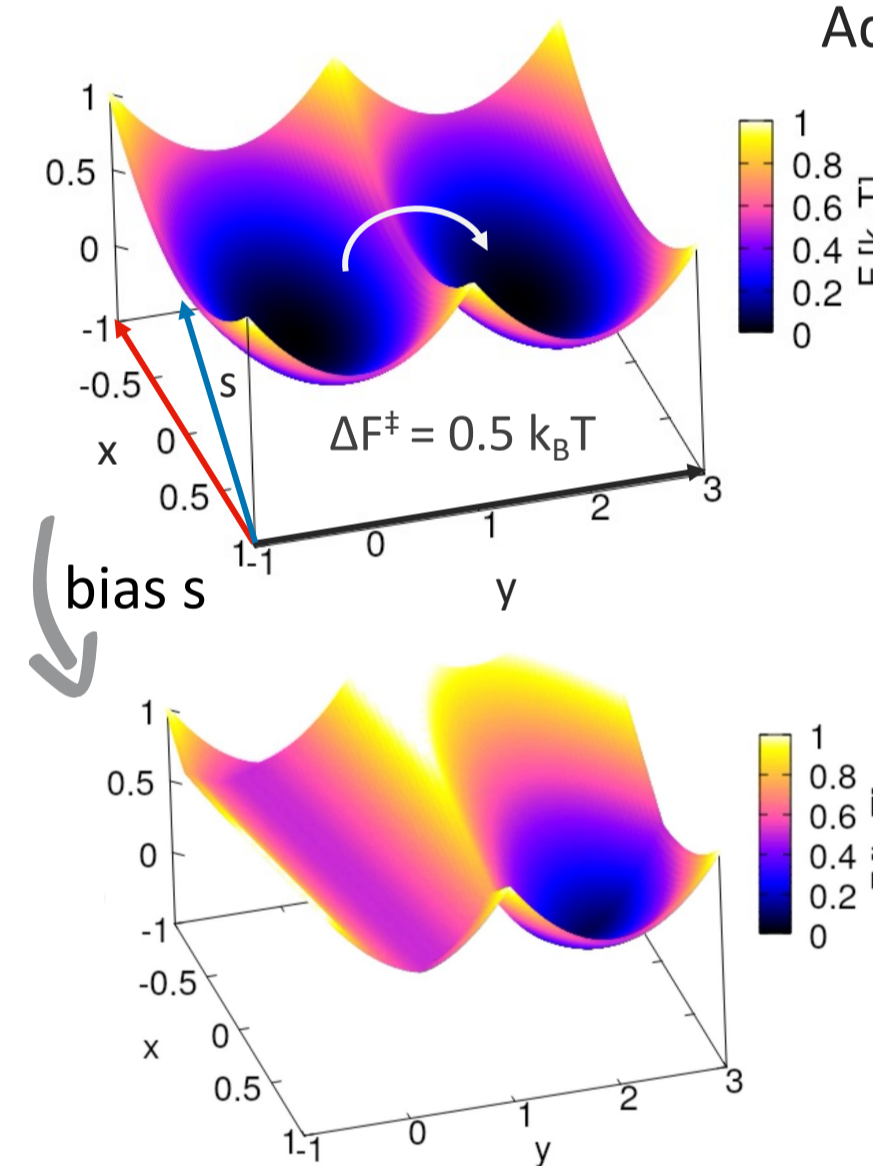
### How does it work?

In MetaD, the time-dependent effective barrier depends on the CV being biased. We estimated the effective barrier for a  $V_{MB} \leq \Delta F^\ddagger$  in a 2D potential energy surface.  $\gamma$  estimates how much of the bias is helping to accelerate the transition.

### 2D double-well landscape

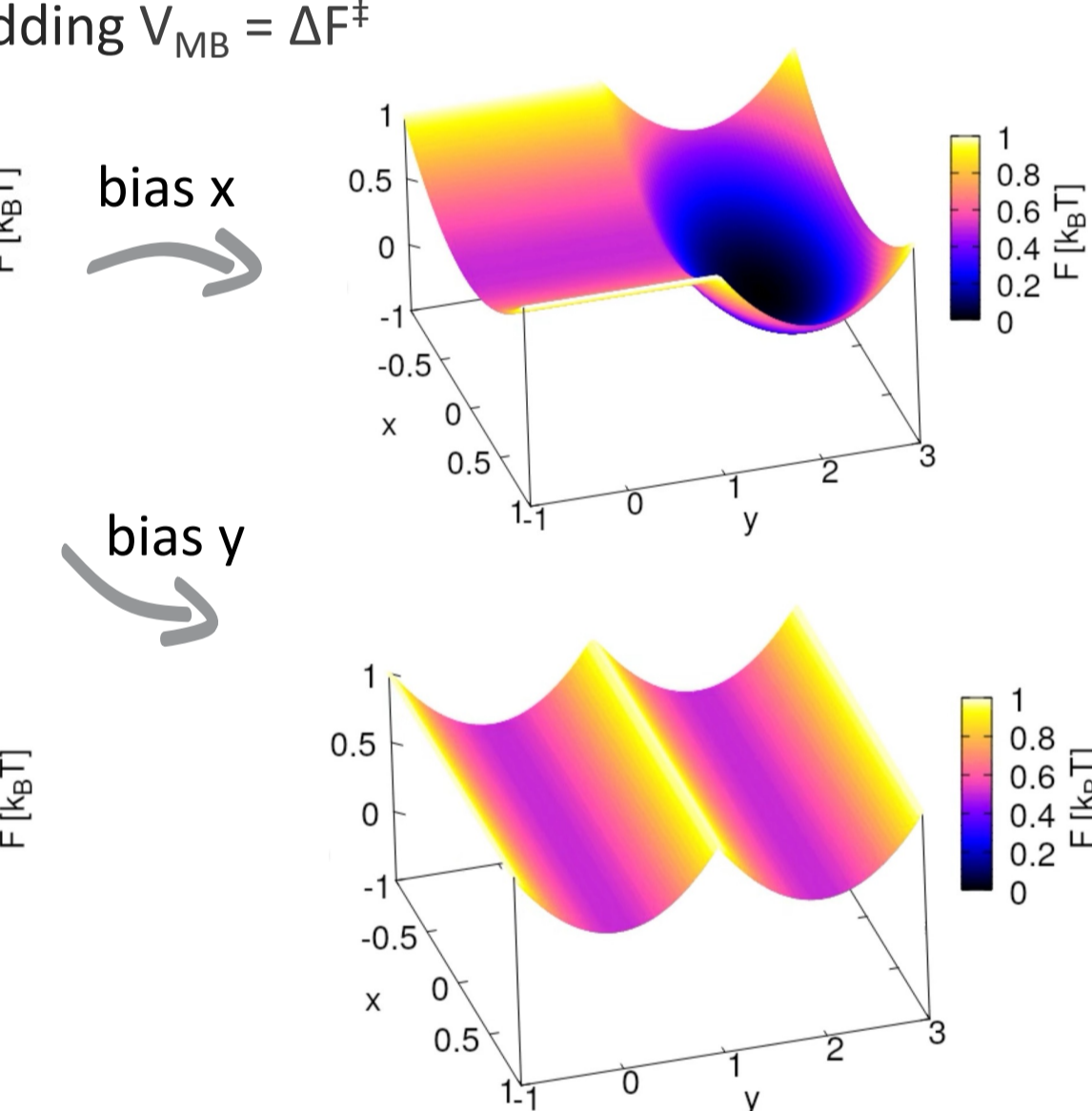
Benchmark system that allows assessing the effect of the CV quality. We compare the rate estimated by our method (KTR) and that of the state-of-the-art infrequent metadynamics<sup>3</sup> (iMetaD) method.

### 2D potential

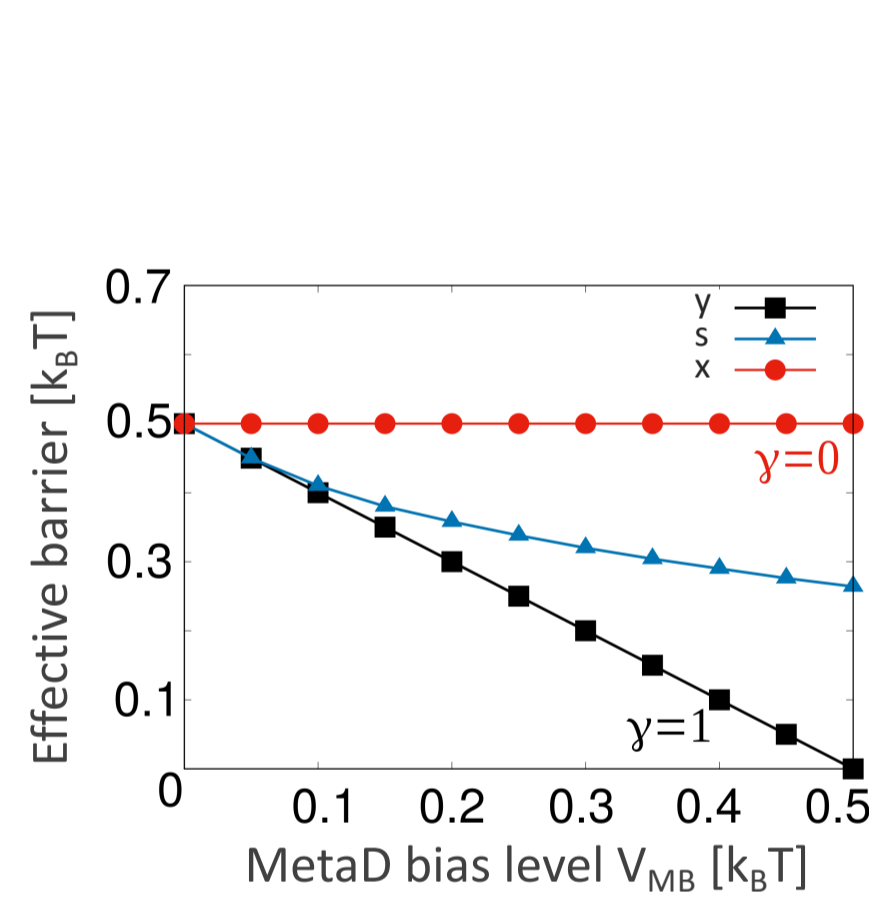


### Potential felt by the system

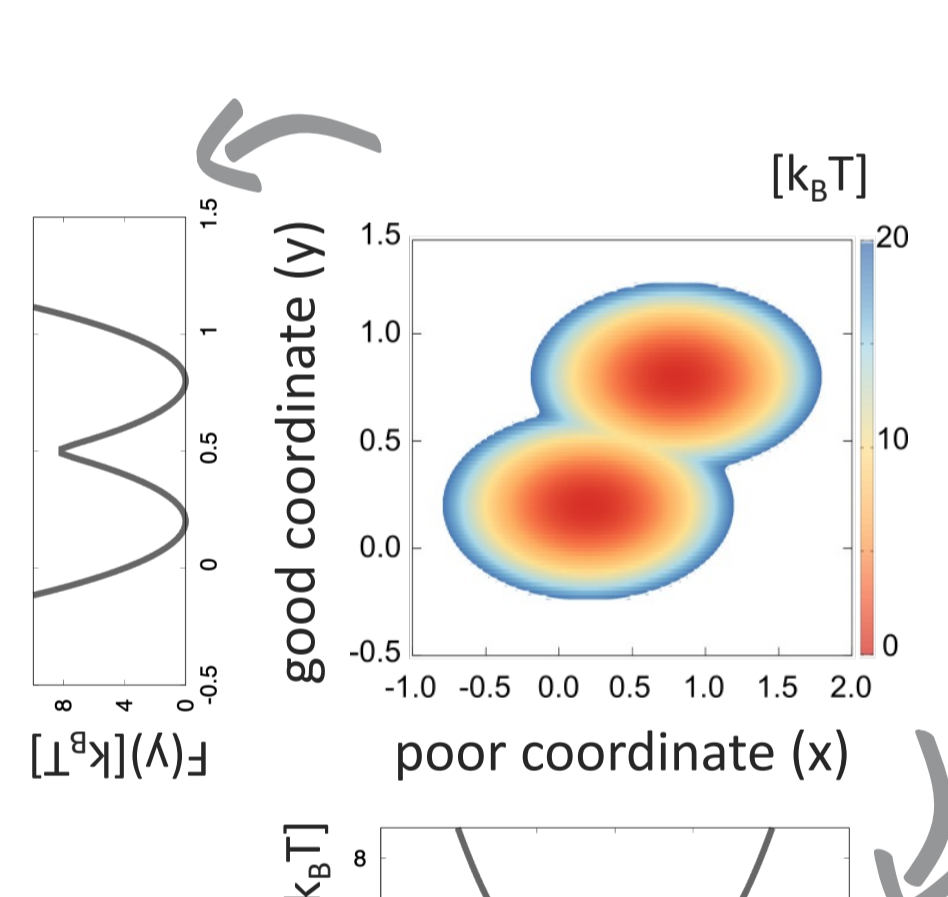
Adding  $V_{MB} = \Delta F^\ddagger$



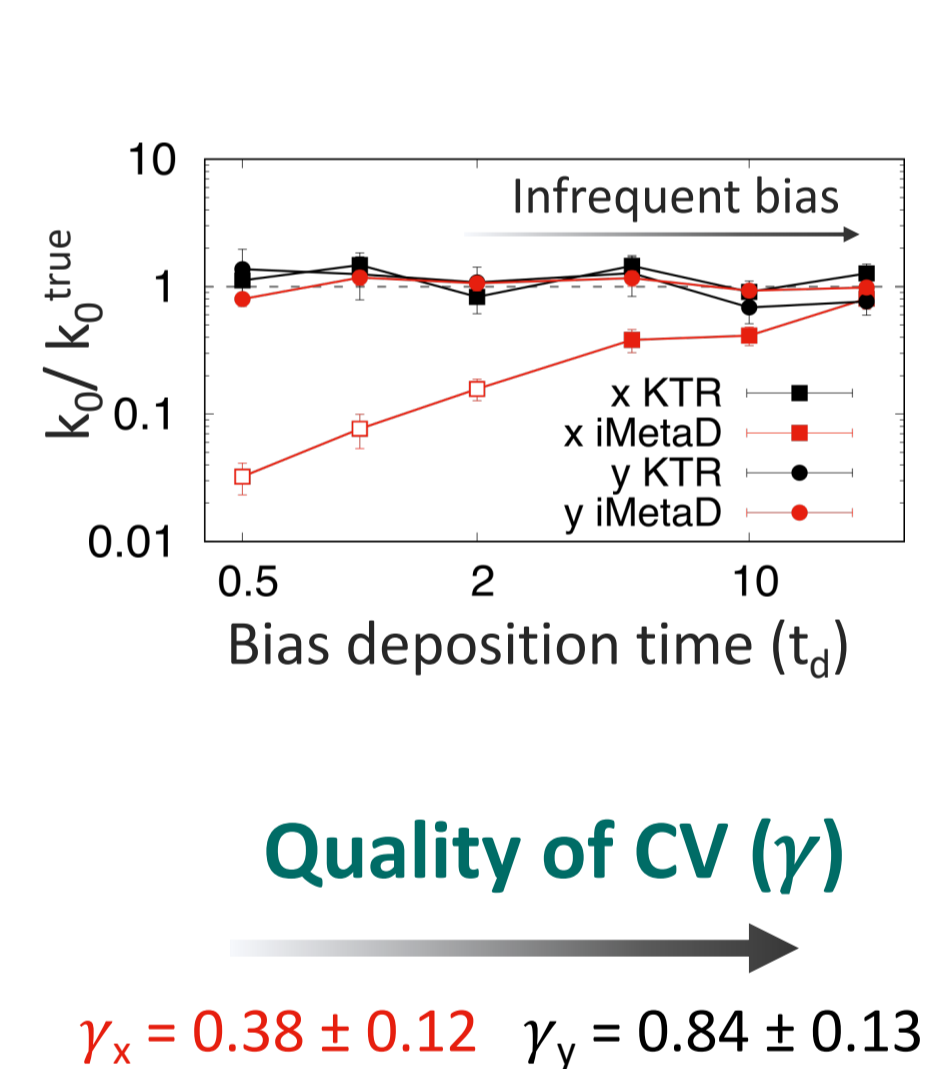
### Effective barrier



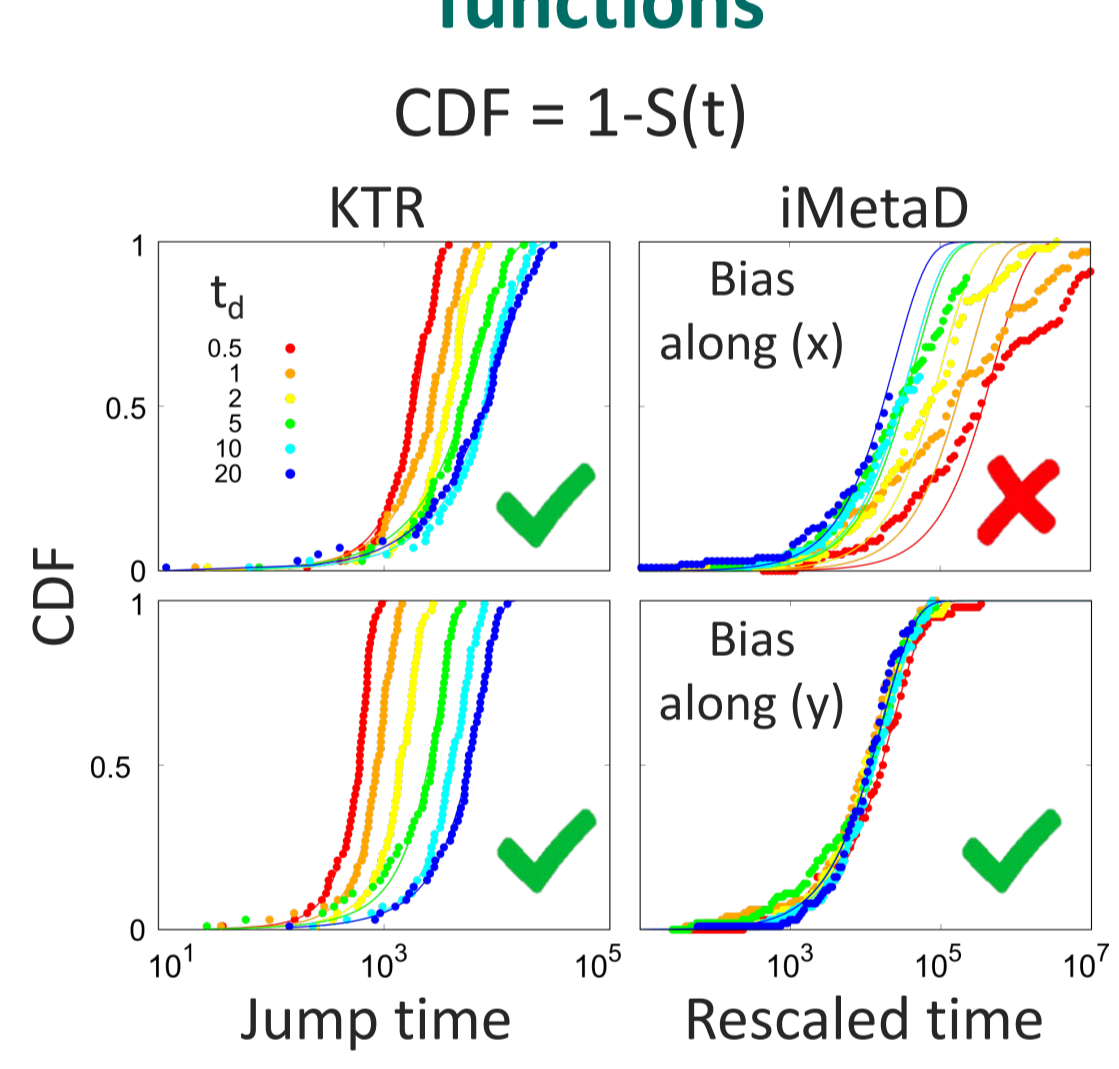
### Free energy profiles



### Kinetic rate ( $k_0$ )



### Cumulative distribution functions



For equal deposited bias, the better the CV, the smaller the effective barrier.  $\gamma$  scales the maximum bias allowing us to work with sub-optimal CVs.

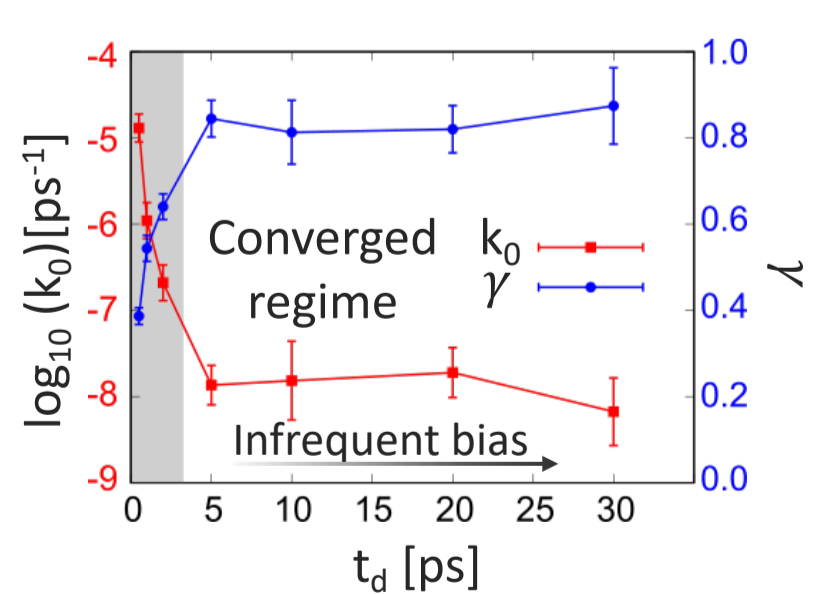
KTR outperforms iMetaD even for poor CVs.  $\gamma$  corrects the effect of poor biasing directions and gives indication of the CV quality.

### Fullerene dimerization

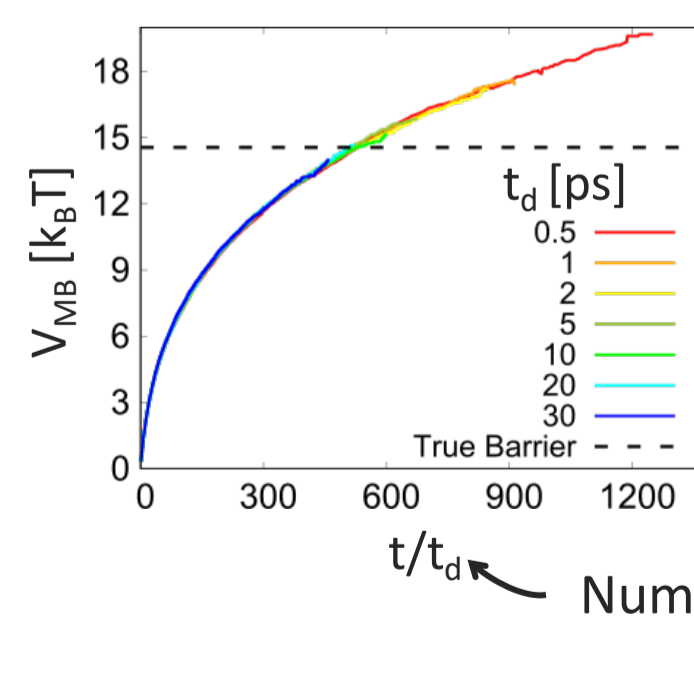
$C_{240}$  dimer in water displays a single-well free energy landscape with a dissociation barrier of  $\sim 14 k_B T$ .

Fullerene  $C_{240}$  dimer in explicit solvent

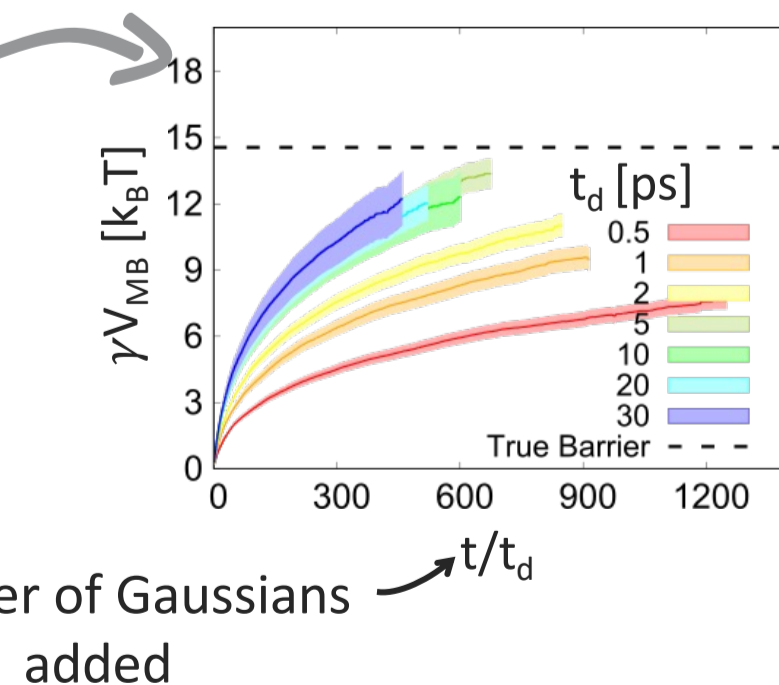
$\gamma$  gets lower to compensate overbias



When  $t_d$  is small the system is overbiased



$\gamma V_{MB}$  is the same for all acceptable values of  $t_d$

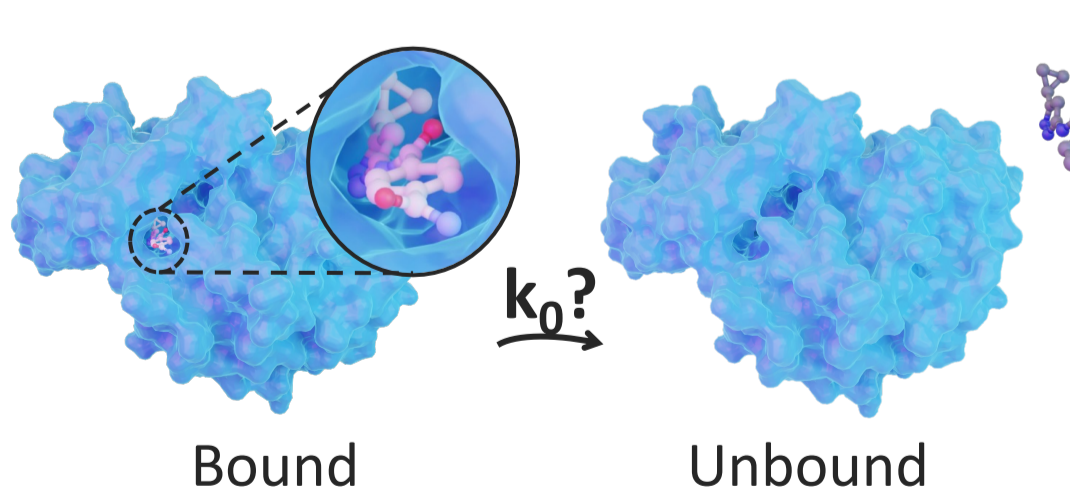


As a reliability test, we can plot  $\gamma V_{MB}$  for different  $t_d$ : at convergence,  $\gamma$  and  $k_0$  do not depend on  $t_d$  and the graphs overlap.

### Protein-ligand unbinding

CDK2 is involved in cell cycle and has been a target for anti-cancer drugs. CDK2-ligand unbinding displays a complex multi-state landscape.

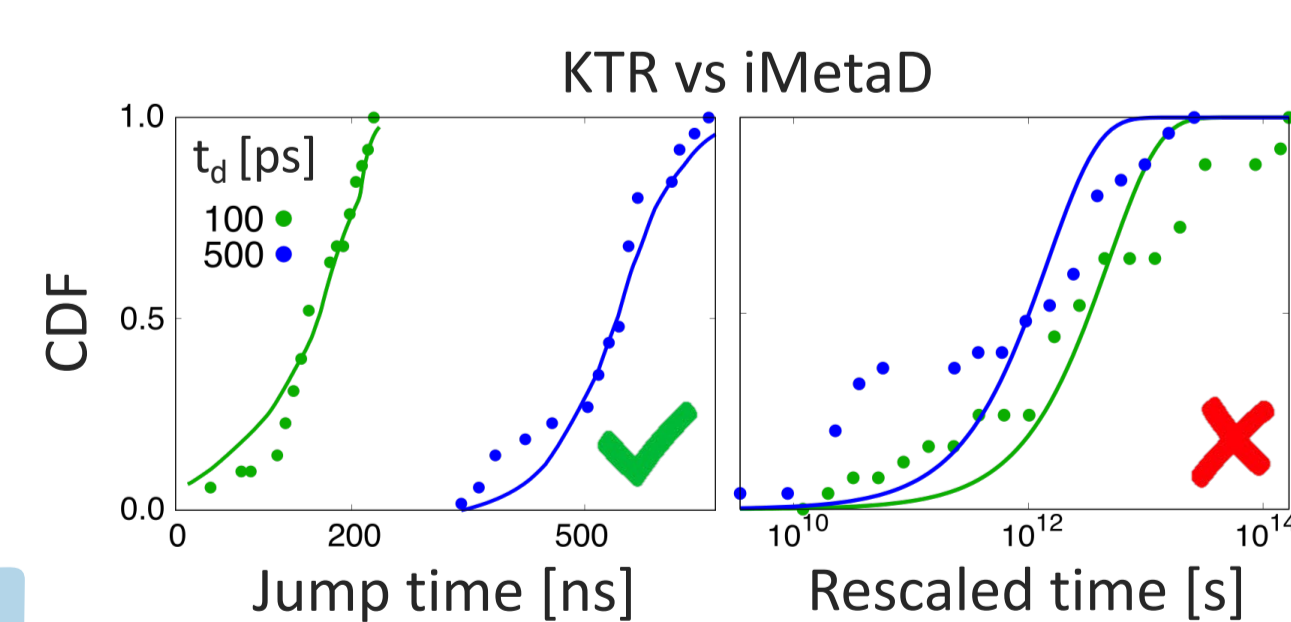
Cyclin-dependent kinase 2 (CDK2) bound to ligand O3K in explicit solvent



### Unbinding rate

$t_d = 100$  ps  
 $k_0 = 8 \pm 6$  s<sup>-1</sup>  
 $\gamma = 0.65 \pm 0.06$   
 $t_d = 500$  ps  
 $k_0 = 5 \pm 3$  s<sup>-1</sup>  
 $\gamma = 0.61 \pm 0.11$   
 $k_0^{exp} = 0.26 \pm 0.05$  s<sup>-1</sup>

### CDFs



We recover unbinding rate up to one order of magnitude accuracy using non-optimal CVs

## CONCLUSIONS

At convergence, KTR yields **accurate rates**.  $\gamma$  simultaneously gives insights about the **efficacy of the CV** and corrects the height of the barrier.

**Limitations:** i) The method is **restricted to single transitions**, extension to multi-state systems required. ii) The **accuracy depends on  $t_d$** .

**Advantages:** Only **single-transition** trajectories required: the **CV quality** can be assessed in post-processing. **Useful for CV optimization**.

## REFERENCES

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- Laio, & Parrinello. *PNAS.* (2002).
- Tiwary, & Parrinello. *PRL.* (2013).
- Hummer, & Szabo. *Biop. J.*, (2003).
- Salvalaglio, Tiwary, & Parrinello. *JCTC.* (2014).



Palacio-Rodriguez, Vroylandt, Stelzl, Pietrucci, Hummer, & Cossio. *JPLC.* (2022)

kpalaciorodr/KTR

