

pyABC

A framework for distributed likelihood-free inference

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Multi-scale models

	Boolean / Petri net models	Constraint-based models	Markov chain models	SDE models	ODE models	PDE models	Agent-based models	
whole-heart (tissue and fluid mechanics, signaling)							Hunter and Borg, <i>Nature Reviews Molecular Cell Biology</i> , 4(3):237-243, 2003	
cancer growth (signaling, cell division and death, angiogenesis, tissue remodeling)							Anderson and Quaranta, <i>Nature Reviews Cancer</i> , 8(3):227-234, 2008	
liver lobule (cell division and cell death, tissue mechanics)								Hoehme et al., <i>PNAS</i> , 107(23):10371-10376, 2010
glucose-insulin-glucagon regulation (blood and interstitial flow, organ uptake, signaling)								Schaller et al., <i>CPT: Pharmacometrics and Systems Pharmacology</i> , 2:e65, 2013
whole-cell (transcription, translation, DNA replication, metabolism, replication)								Karr et al., <i>Cell</i> , 150(2):389-401, 2012

¹[Hasenauer, *Data-driven modeling of biological multi-scale processes*, J. Coup. Sys. and Mult. Dyn., 2015]

Example: Multi-scale model of tumor growth¹

proliferating cells

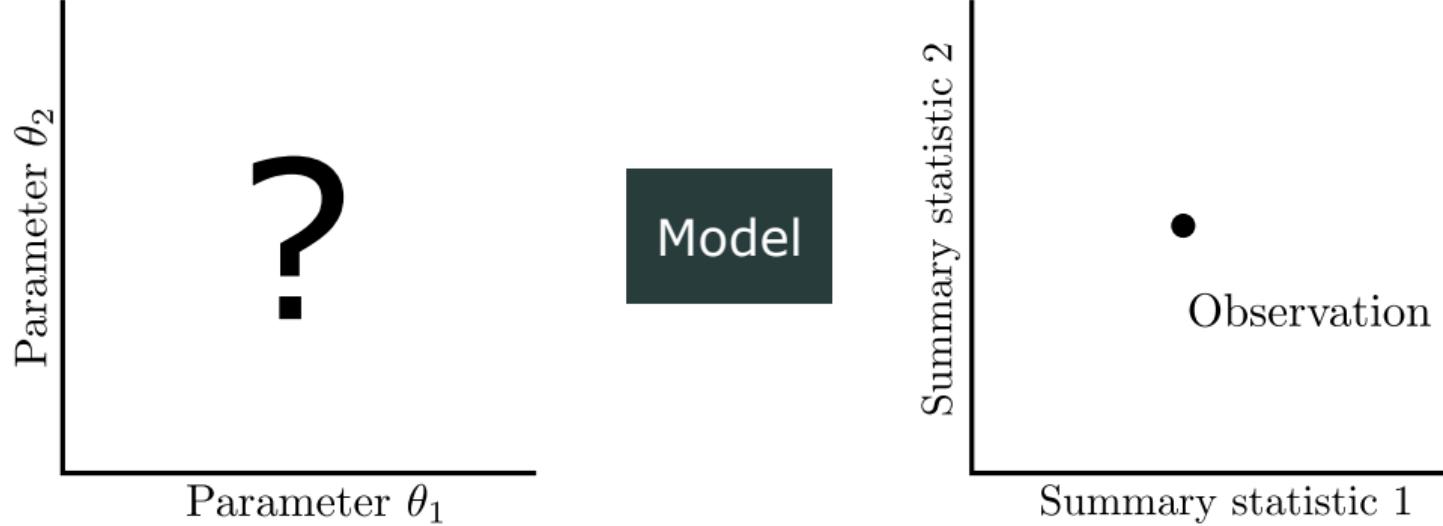
- ▶ Hybrid discrete-continuous model
- ▶ Cells modeled as interacting agents, dynamics of extracellular substances by reaction-diffusion equations
- ▶ Simulate up to 10^6 cancer cells
- ▶ 10s - 1h for one forward simulation

¹[Jagiella et al., *Parallelization and high-performance computing enables automated statistical inference of multi-scale models*, Cell Systems, 2017]

How to do parameter inference for stochastic multi-scale models?

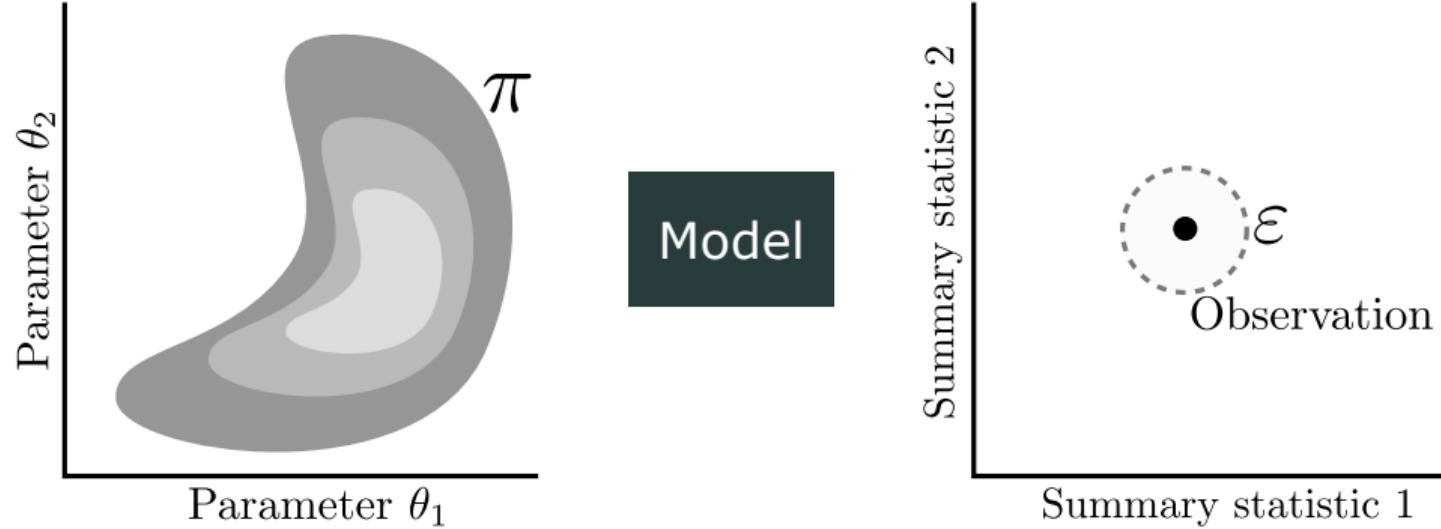
Rejection ABC

Principle of Approximate Bayesian Computation



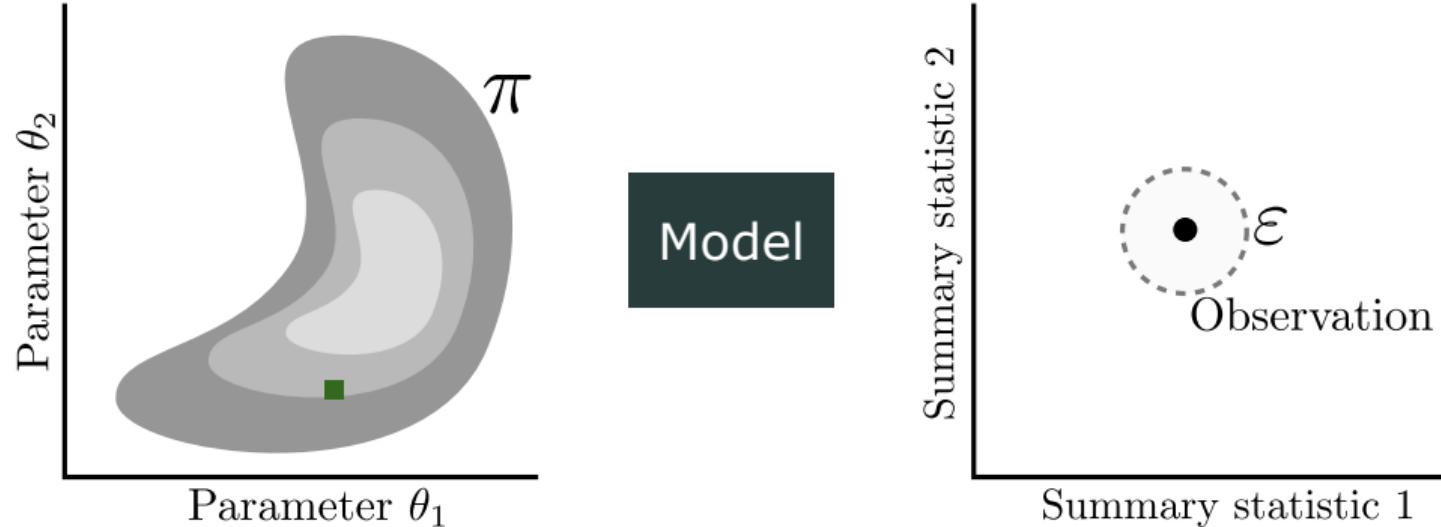
Rejection ABC

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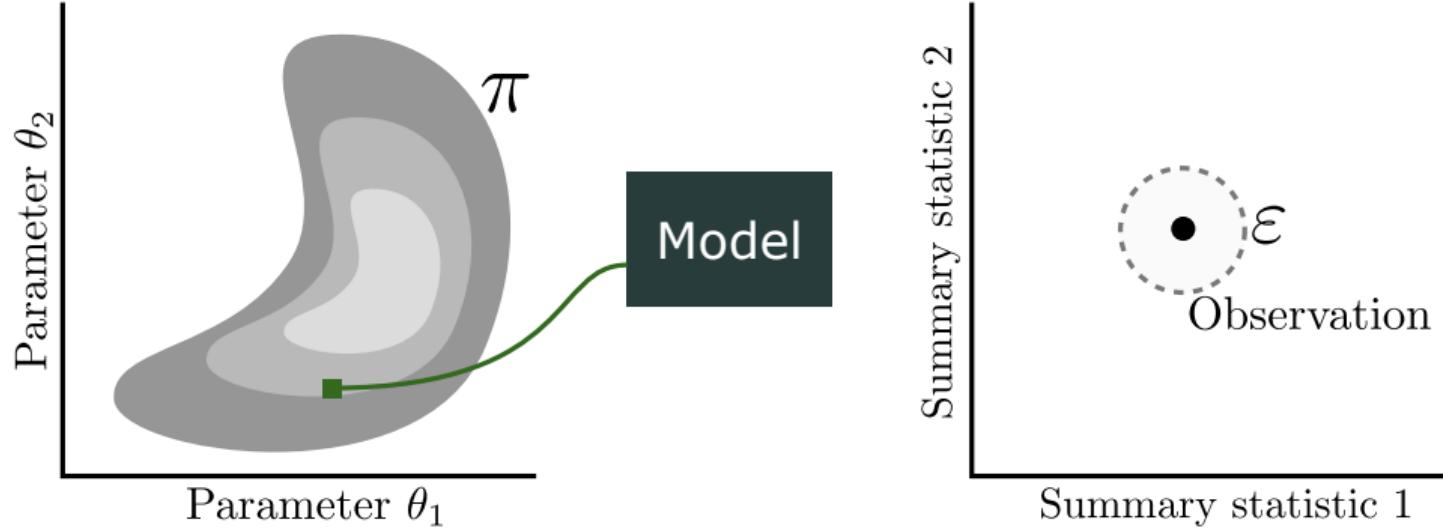
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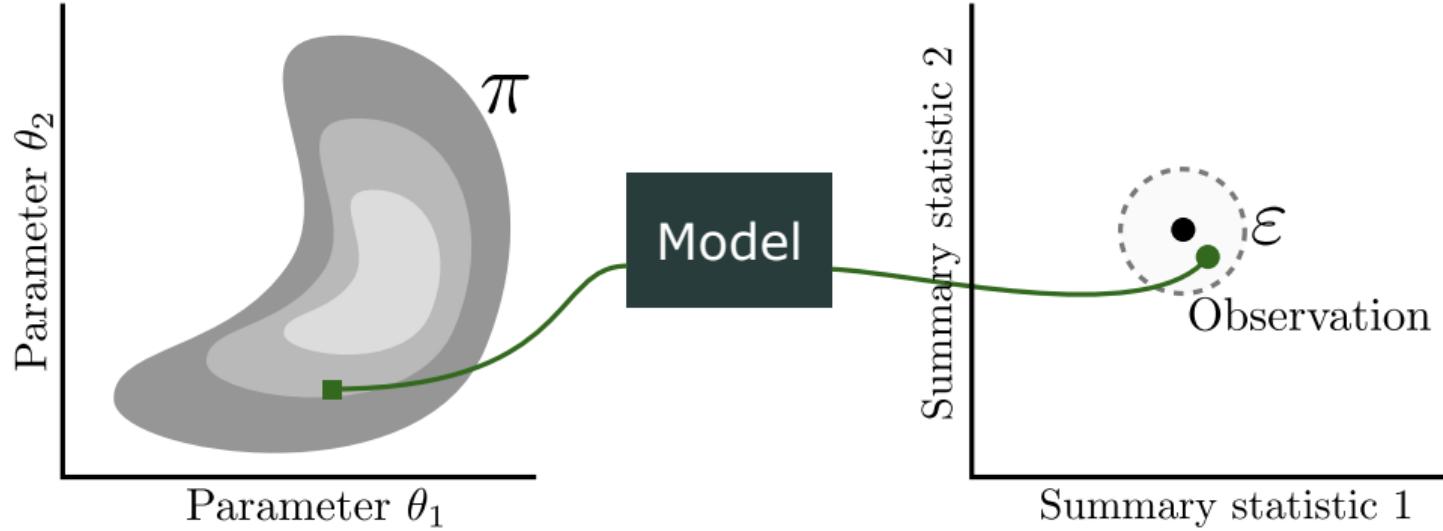
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Principle of Approximate Bayesian Computation



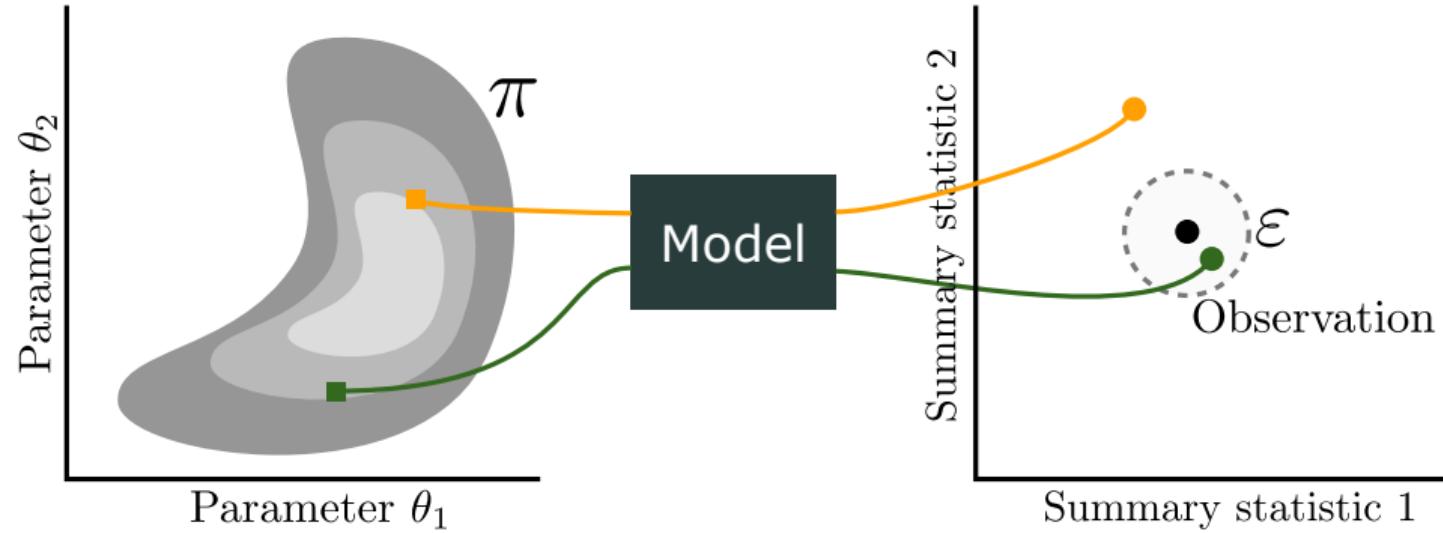
Rejection ABC

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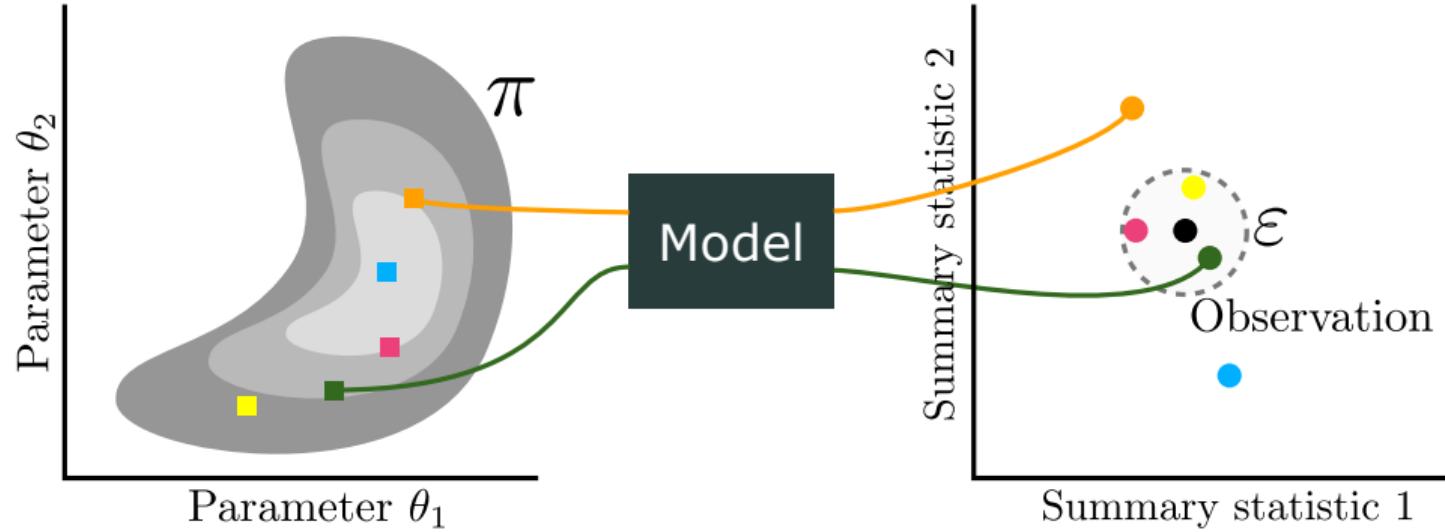
Rejection ABC

Principle of Approximate Bayesian Computation



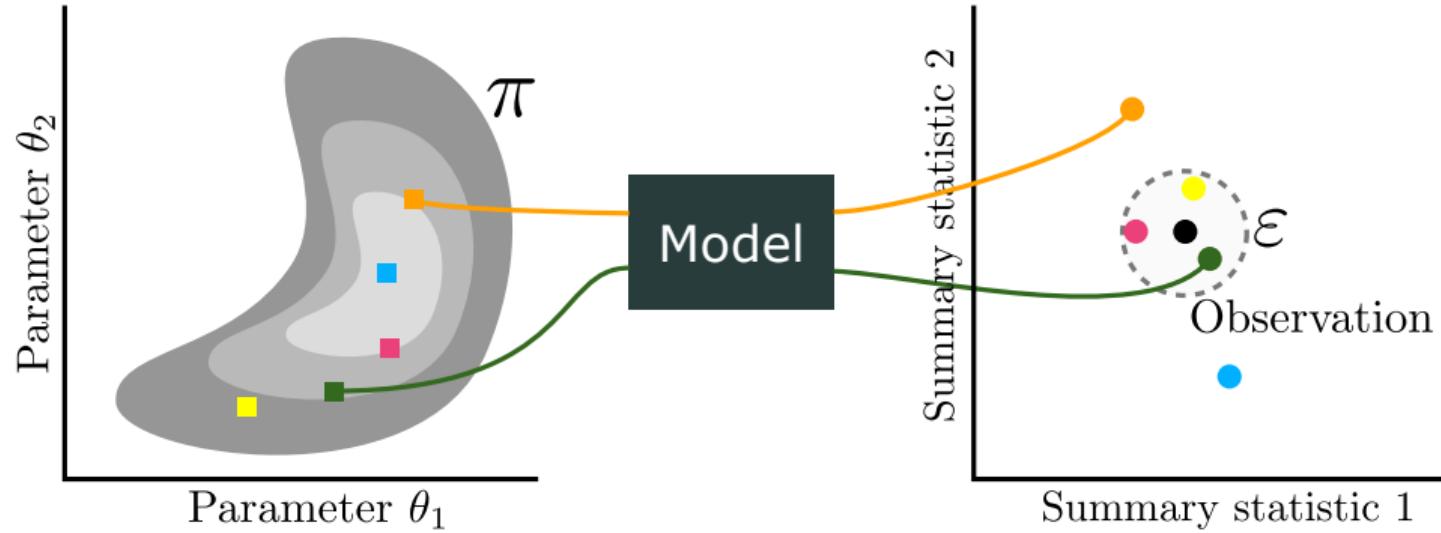
Rejection ABC

Principle of Approximate Bayesian Computation



Rejection ABC

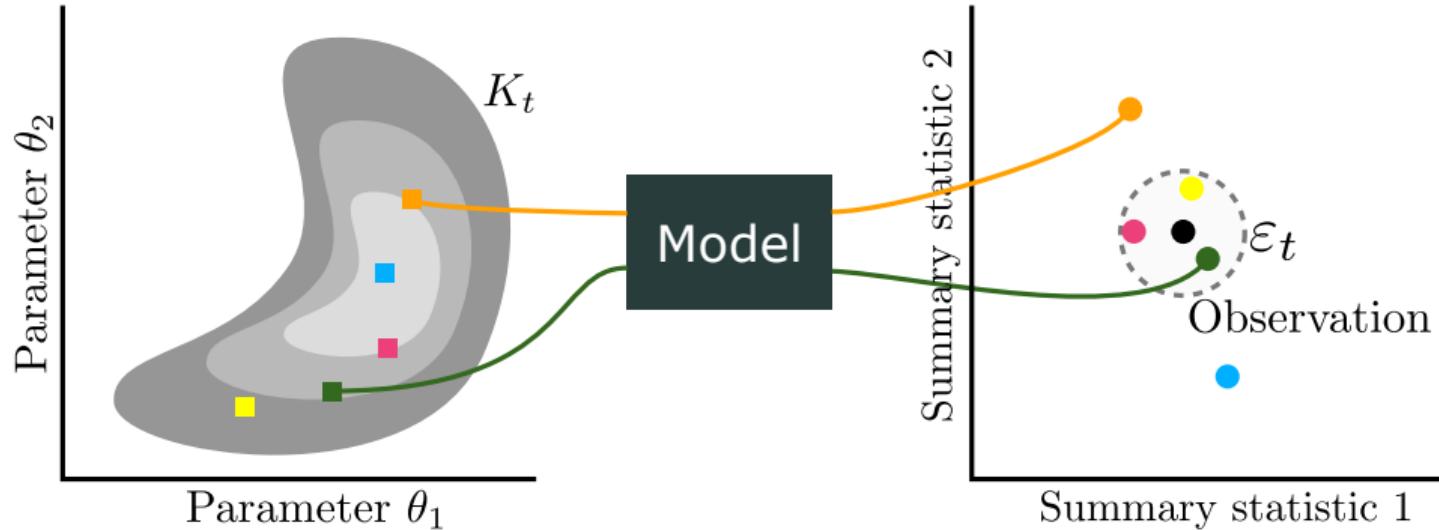
Principle of Approximate Bayesian Computation



- ▶ Approximation error
- ▶ Inefficient

ABC-SMC¹

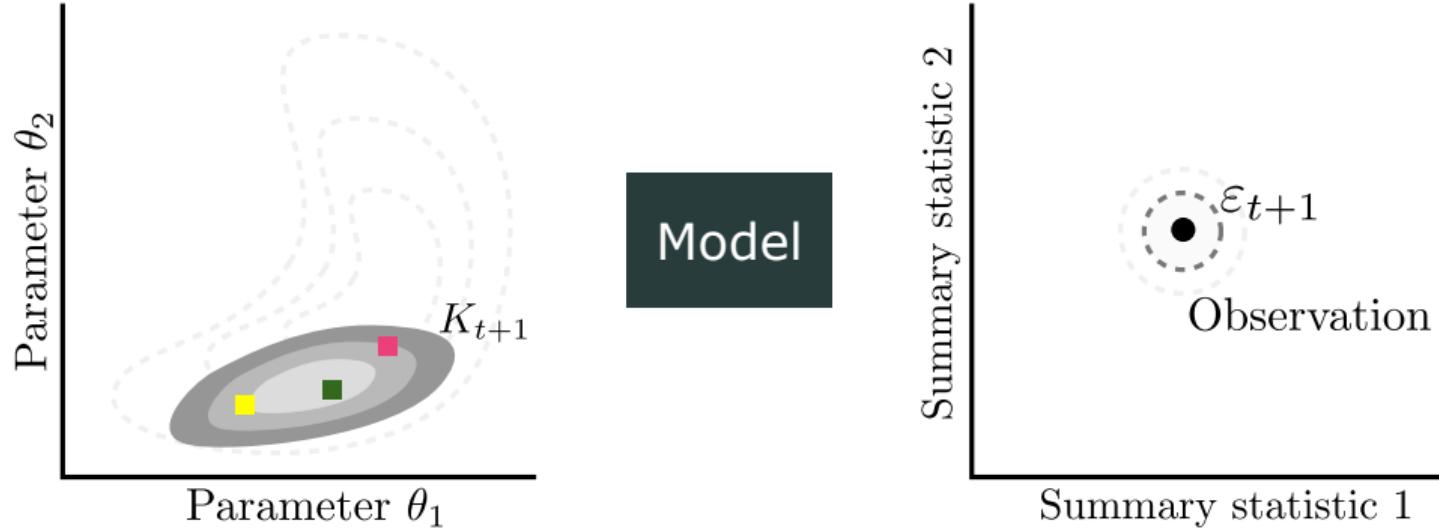
Combine with a Sequential Monte Carlo scheme



¹[Toni, Stumpf, ABC scheme for parameter inference and model selection in dynamical systems, J. R. Soc., 2009]

ABC-SMC¹

Combine with a Sequential Monte Carlo scheme



¹[Toni, Stumpf, ABC scheme for parameter inference and model selection in dynamical systems, J. R. Soc., 2009]

pyABC¹

<https://github.com/icb-dcm/pyabc>



user-friendly



scalable



flexible

¹[Klinger, Rickert, Hasenauer, *pyABC: distributed, likelihood-free inference*, Bioinformatics, 2018]



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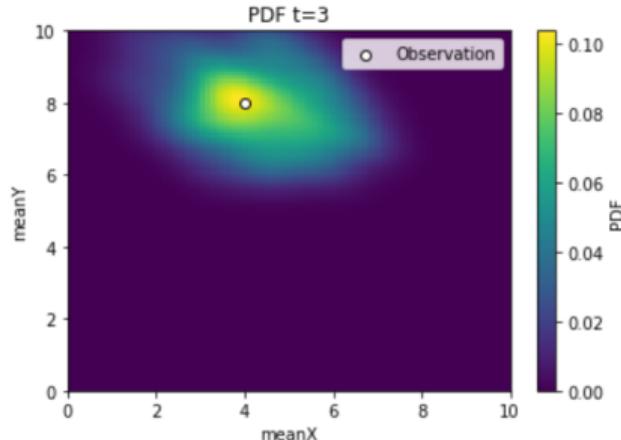
flexible

Three lines get you started

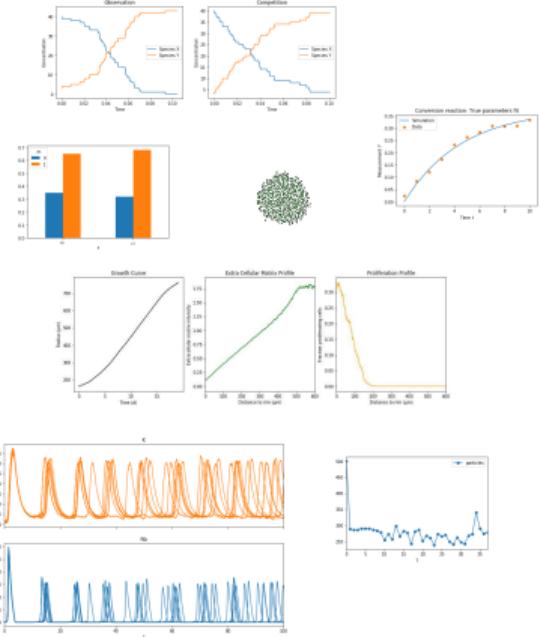
```
# model data
abc = pyabc.ABCSMC(model, prior, distance)

# observations
abc.new("sqlite:///database.db", observations)

# run the abc
abc.run(minimum_epsilon=1e-2, max_nr_populations=30)
```



If you need help ...



- ... 10+ application examples
- ... extensive documentation
- ... ask us



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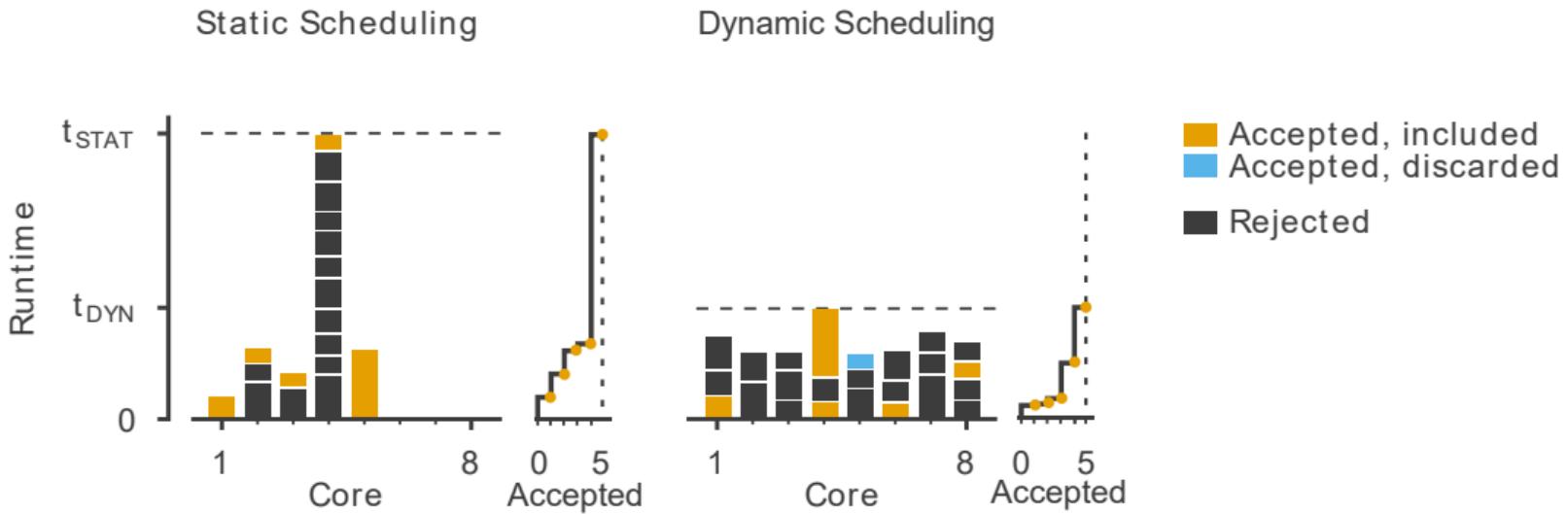


flexible

Parallel backends: 1 to 1000s of cores



Parallelization strategies¹



¹[Klinger, Hasenauer, *A scheme for adaptive selection of population sizes in ABC-SMC*, CMSB Proceedings, 2017]



user-friendly



scalable



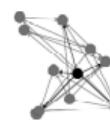
flexible

Many customization possibilities

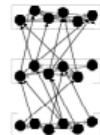
- ▶ Model selection



Model 1



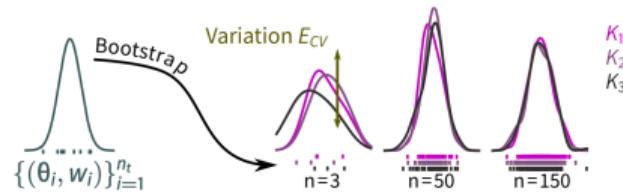
Model 2



Model 3

Many customization possibilities

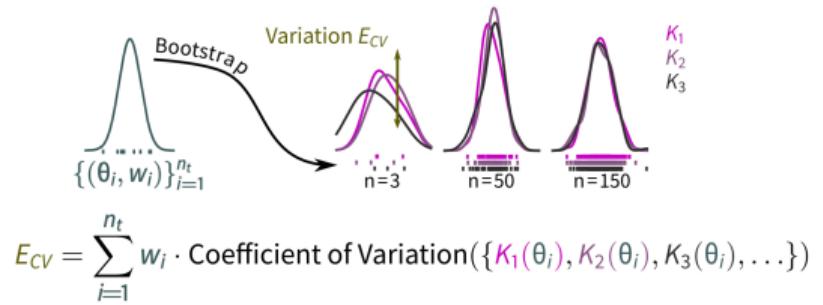
- ▶ Model selection
- ▶ Adaptive population sizes



$$E_{CV} = \sum_{i=1}^{n_t} w_i \cdot \text{Coefficient of Variation}(\{K_1(\theta_i), K_2(\theta_i), K_3(\theta_i), \dots\})$$

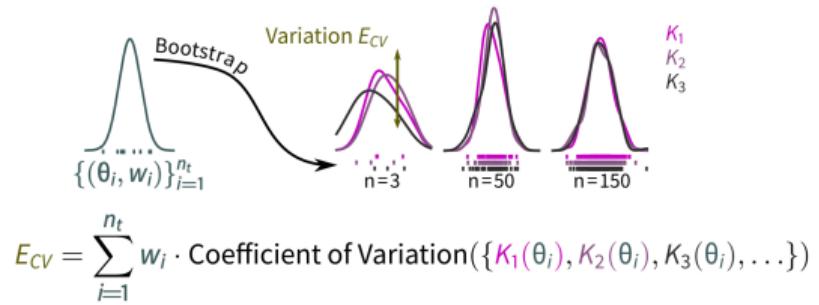
Many customization possibilities

- ▶ Model selection
- ▶ Adaptive population sizes
- ▶ Adaptive acceptance thresholds



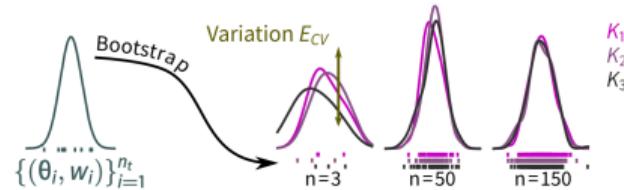
Many customization possibilities

- ▶ Model selection
- ▶ Adaptive population sizes
- ▶ Adaptive acceptance thresholds
- ▶ Adaptive distance functions



Many customization possibilities

- ▶ Model selection
- ▶ Adaptive population sizes
- ▶ Adaptive acceptance thresholds
- ▶ Adaptive distance functions
- ▶ Global and local transition kernels
- ▶ Early rejection
- ▶ Noise assessment

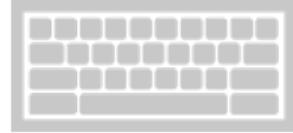


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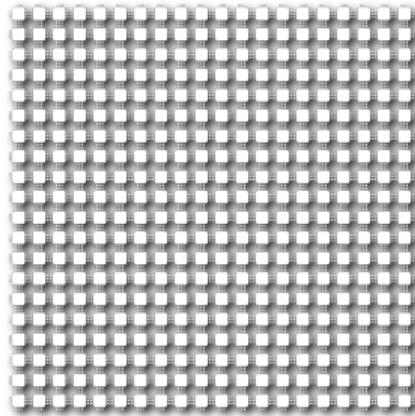
Many customization possibilities

- ▶ Model selection
- ▶ Adaptive population sizes
- ▶ Adaptive acceptance thresholds
- ▶ Adaptive distance functions
- ▶ Global and local transition kernels
- ▶ Early rejection
- ▶ Noise assessment

- ▶ Implement your own



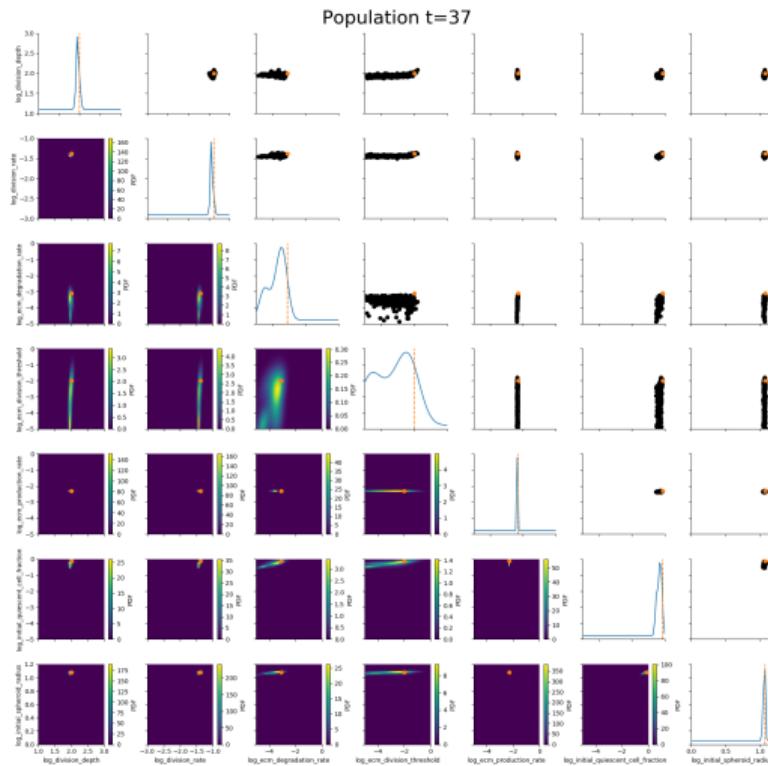
Example: Multi-scale model of tumor growth



- ▶ 400 cores
- ▶ 3 days
- ▶ 1.883.664 simulations

Example: Multi-scale model of tumor growth

Example: Multi-scale model of tumor growth



Summary

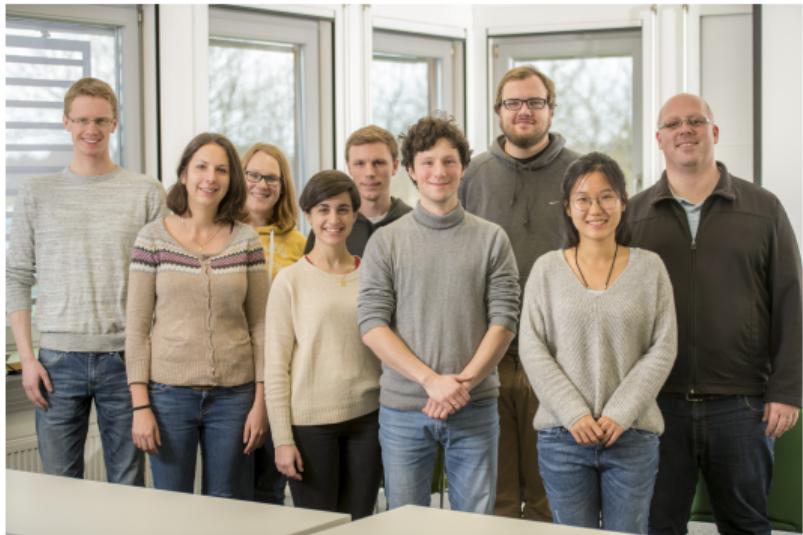
- ▶ Parameter estimation when we cannot evaluate the likelihood is challenging
- ▶ ABC allows for reliable statistical inference
- ▶ pyABC provides a user-friendly, scalable, and flexible framework
- ▶ Already used in multiple applications

<https://github.com/icb-dcm/pyabc>

Acknowledgments

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- ▶ Elba Raimúndez Álvarez
- ▶ Emmanuel Klinger
- ▶ Dennis Rickert
- ▶ Jan Hasenauer
- ▶ Rest of the ICB-DCM group



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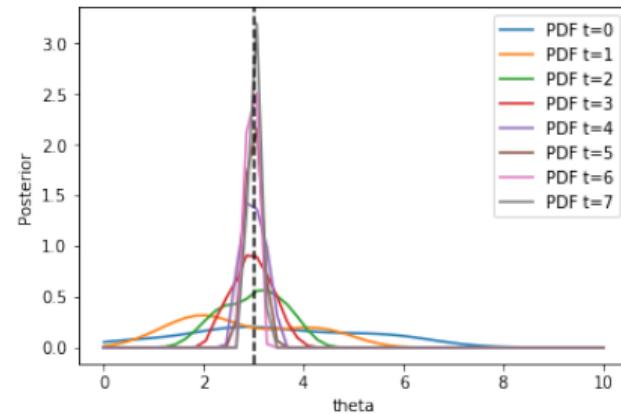
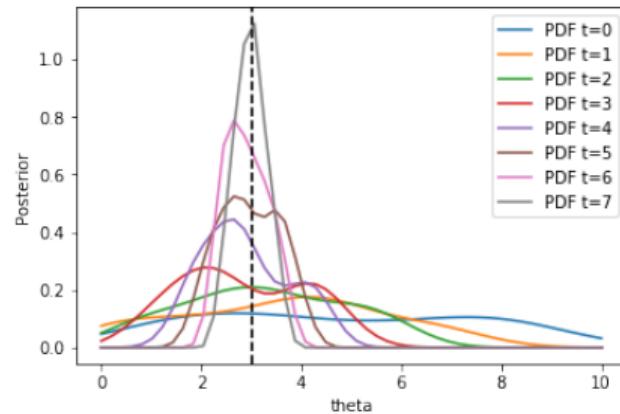


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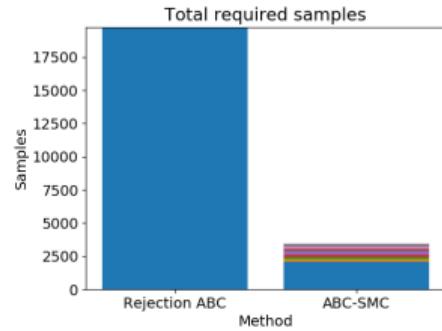
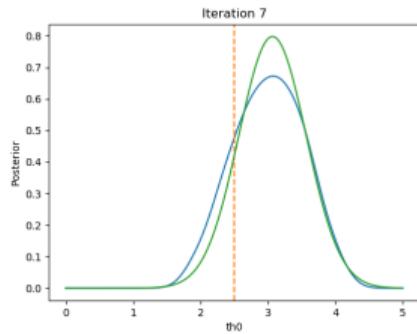
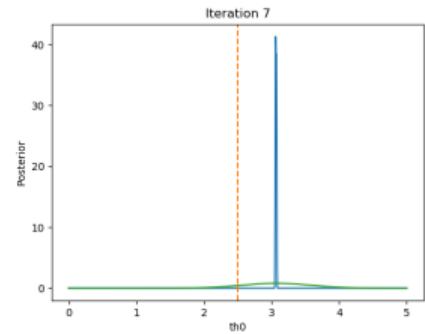
And ...

... adaptive distance functions



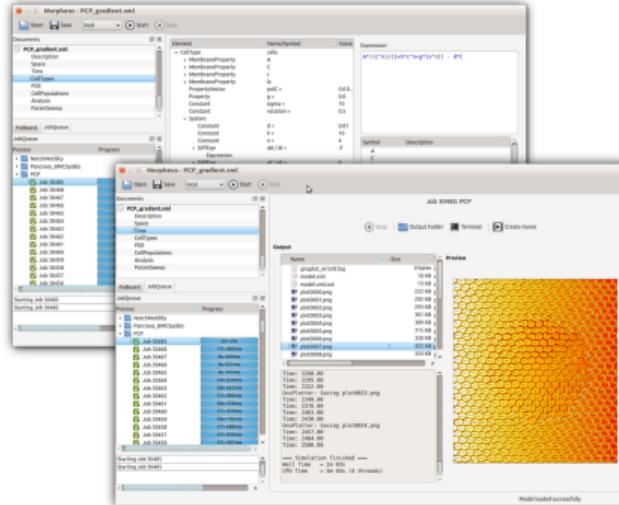
And ...

... noise assessment



And ...

... model construction using Morpheus¹



¹[Staruss et al., *Morpheus: a user-friendly modeling environment for multiscale and multicellular systems biology*, Bioinformatics, 2014]

And ...

... likelihood-free Bayesian inference

$$\pi(\theta|D) = \frac{\pi(D|\theta)\pi(\theta)}{\pi(D)}$$