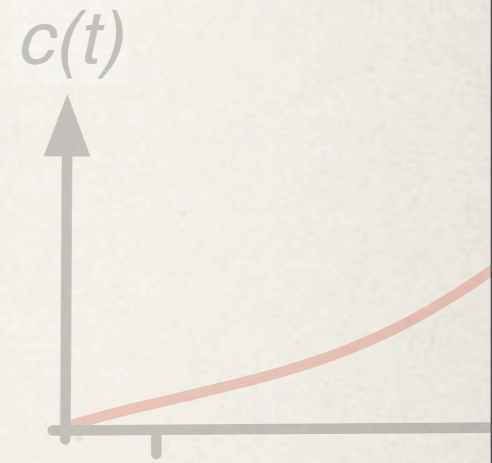
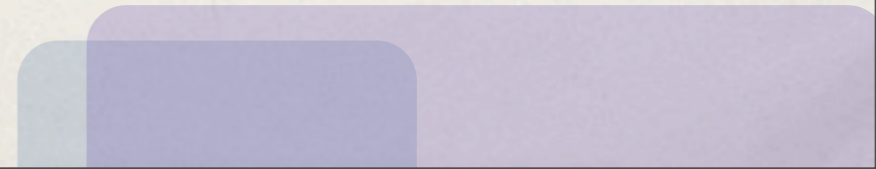


Control of many-body quantum dynamics

Simone Montangero - Ulm University



KITP - 01/03/2013



Optimal control

Optimal control

System

Optimal control



Optimal control

System

Optimal control

System

- ❖ Few-body quantum systems: standard optimal control (high-accuracy, complete knowledge, many iterations...)

H. Rabitz, NJP (2009)
Altafini & Ticozzi IEEE (2012)

Optimal control

System

- ❖ Few-body quantum systems: standard optimal control (high-accuracy, complete knowledge, many iterations...)
- ❖ Many-body?

H. Rabitz, NJP (2009)
Altafini & Ticozzi IEEE (2012)

CRAAB optimization



CRAAB optimization



- ❖ Simple and versatile optimal control technique
- ❖ **Unique** optimal control integrated with tensor network methods (t-DMRG, ...)
- ❖ Works for open systems

CRAAB optimization



- ❖ Simple and versatile optimal control technique
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Control

CRAAB optimization



- ❖ Simple and versatile optimal control technique
 - ❖ **Unique** optimal control integrated with tensor network methods (t-DMRG, ...)
 - ❖ Works for open systems
- Control
- Many body quantum systems

CRAAB optimization



- ❖ Simple and versatile optimal control technique **Control**
- ❖ **Unique** optimal control integrated with tensor network methods (t-DMRG, ...) **Many body quantum systems**
- ❖ Works for open systems **Decoherence**

P. Doria, T. Calarco, SM PRL. (2011)

F. Caruso, et.al. PRA (2012)

T. Caneva, T. Calarco, SM

PRA (2011), NJP (2012)

Chopped RAndom Basis

T. Caneva, T. Calarco, and SM, Phys. Rev. A 2011

Chopped RAndom Basis

Functional
minimization

T. Caneva, T. Calarco, and SM, Phys. Rev. A 2011

Chopped RAndom Basis

Reduced basis method

Functional
minimization

T. Caneva, T. Calarco, and SM, Phys. Rev. A 2011

Chopped RAndom Basis

Expand control field over n_f
“randomized” basis functions

Reduced basis method

Functional
minimization

Chopped RAndom Basis

Expand control field over n_f
“randomized” basis functions

Reduced basis method

Multivariable
function minimization

Functional
minimization

Chopped RAndom Basis

Expand control field over n_f
“randomized” basis functions

Reduced basis method

Multivariable
function minimization

Functional
minimization

Direct Search
methods

Chopped RAndom Basis

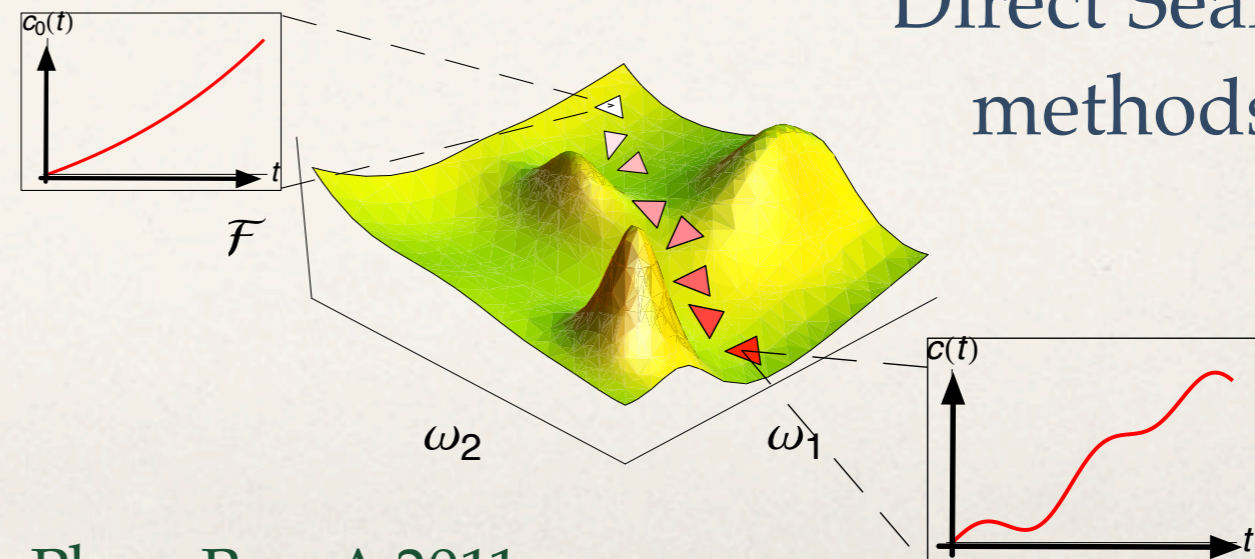
Expand control field over n_f
“randomized” basis functions

Reduced basis method

Multivariable
function minimization

Functional
minimization

Direct Search
methods



T. Caneva, T. Calarco, and SM, Phys. Rev. A 2011

Chopped RAndom Basis

Expand control field over n_f
“randomized” basis functions

Reduced basis method

Multivariable
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Functional
minimization

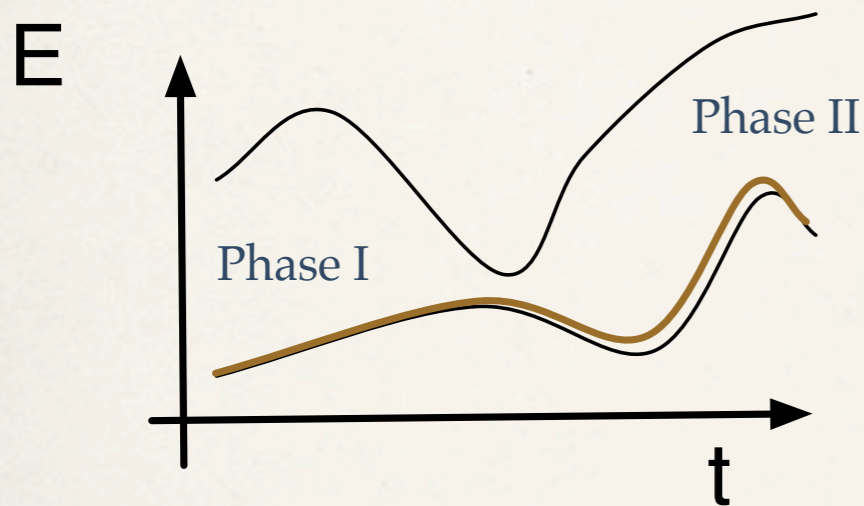
Direct Search
methods

$O(10)$ parameters!

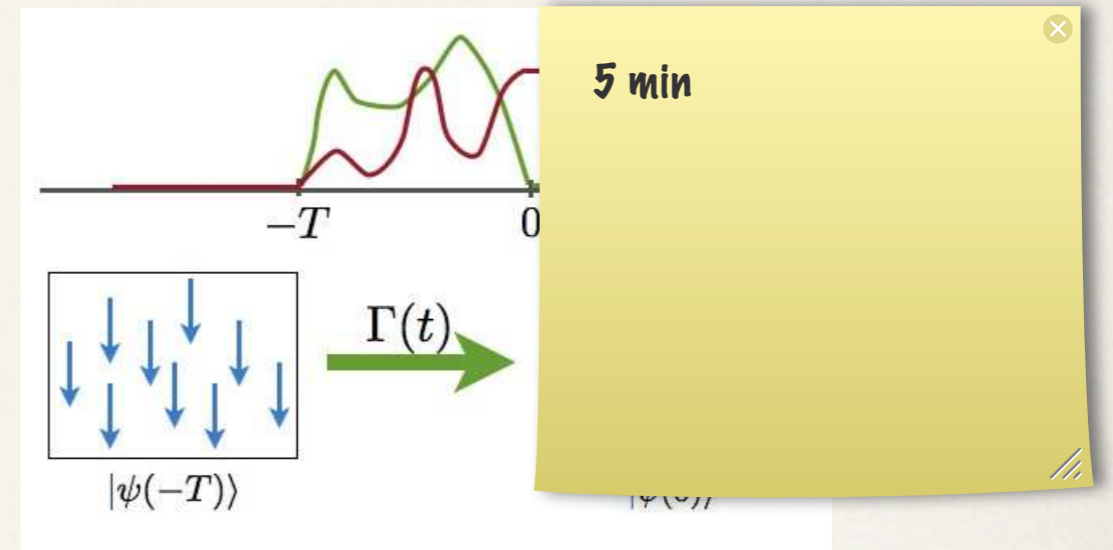


T. Caneva, T. Calarco, and SM, Phys. Rev. A 2011

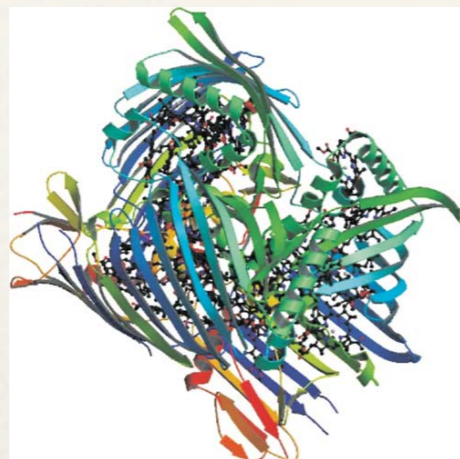
Applications



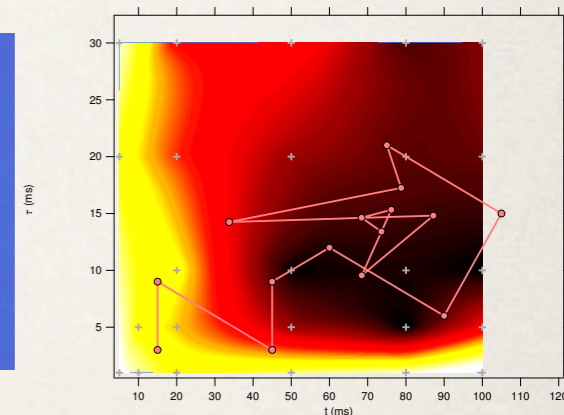
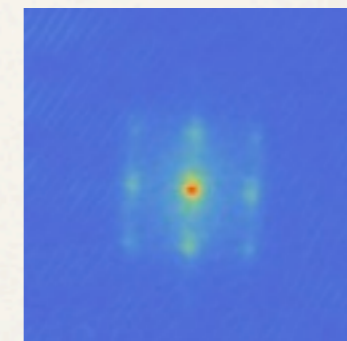
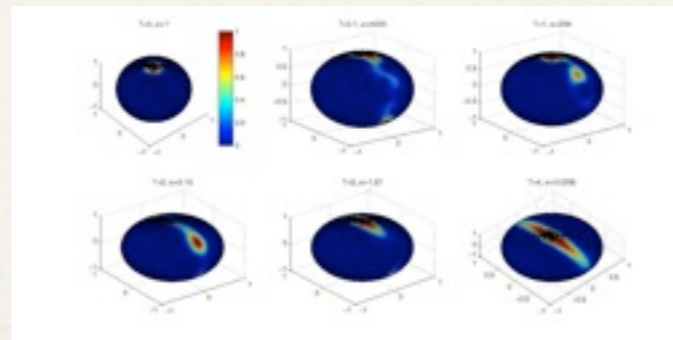
Quantum Phase Transition dynamics



Entanglement Storage units

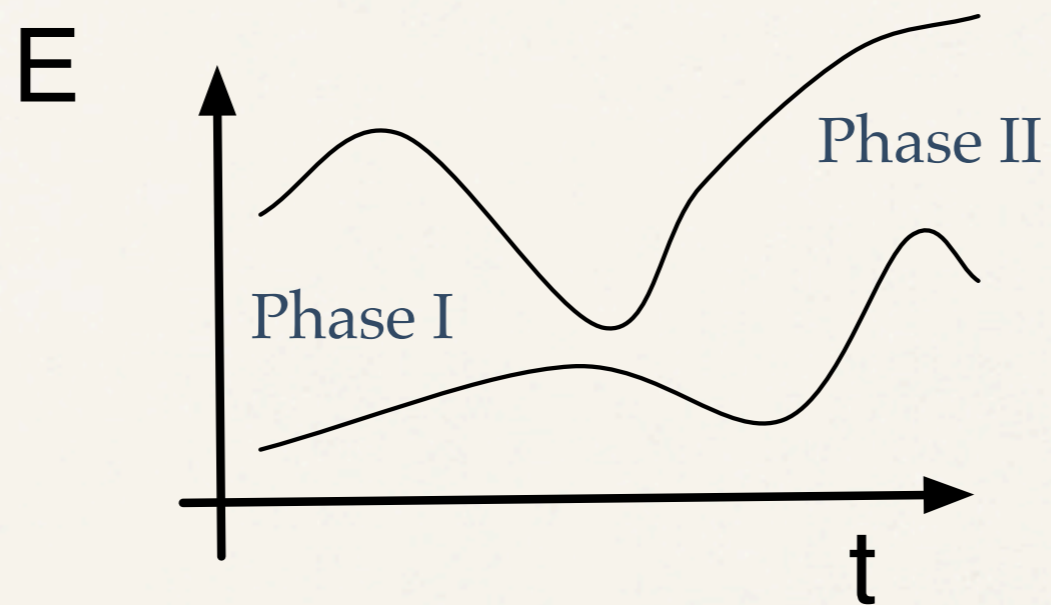


Light-harvesting dynamics

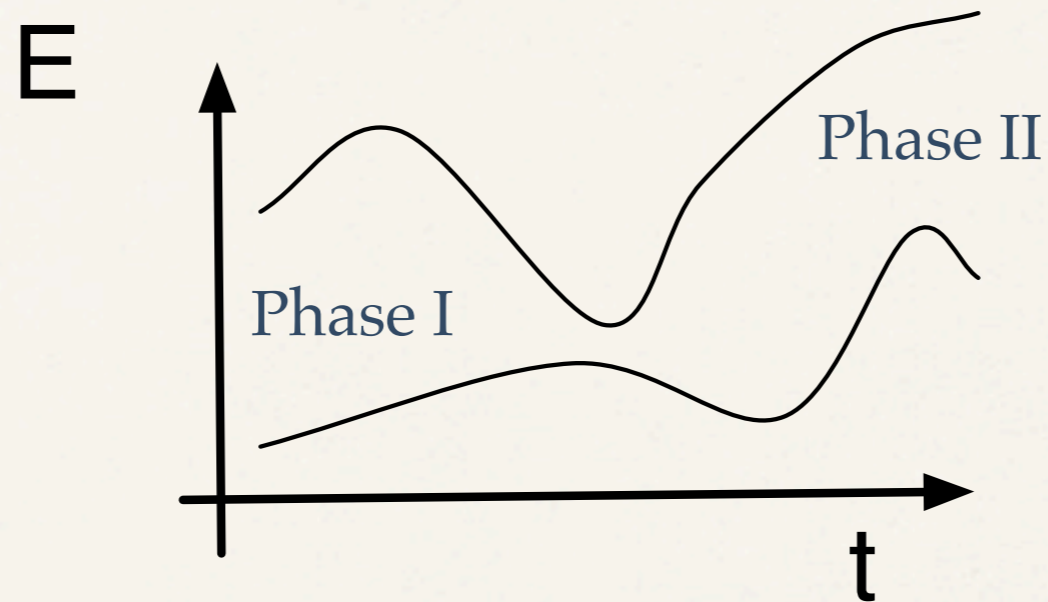


Experiment optimization

Control of QPT dynamics



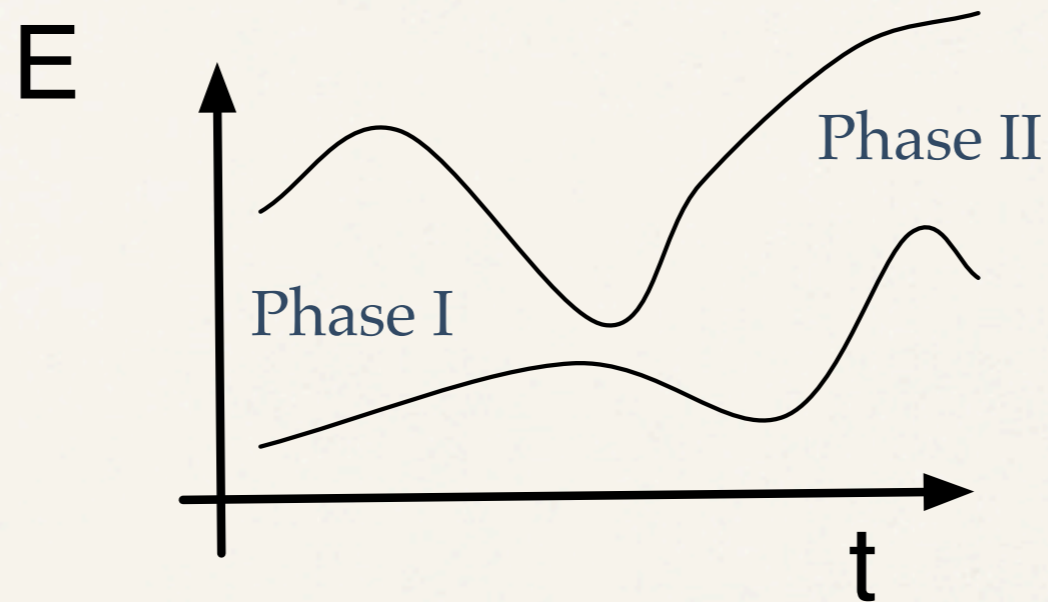
Control of QPT dynamics



Adiabatic
strategy

Control of QPT dynamics

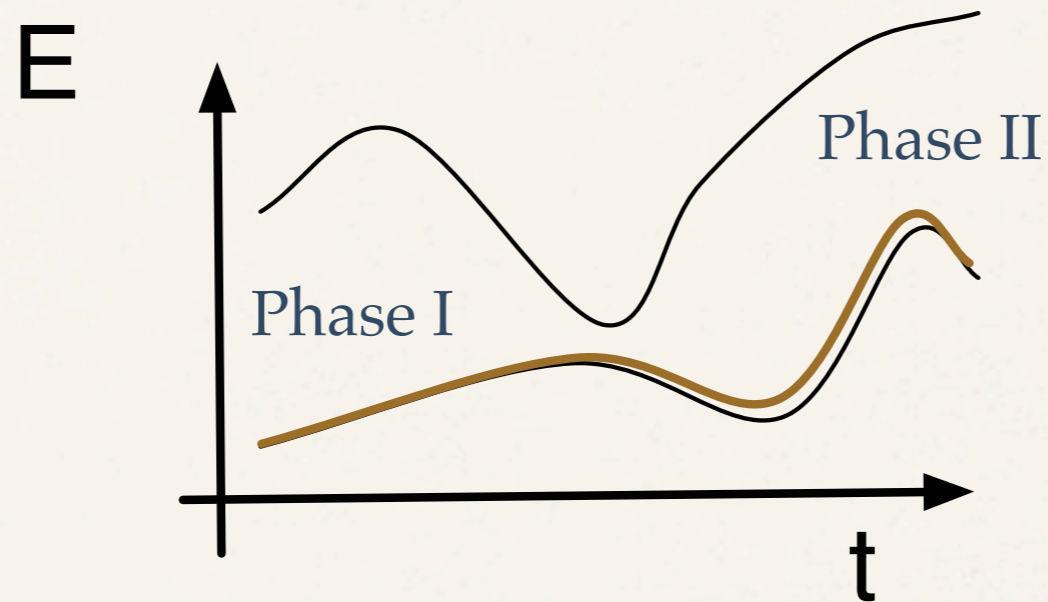
Slow



Adiabatic
strategy

Control of QPT dynamics

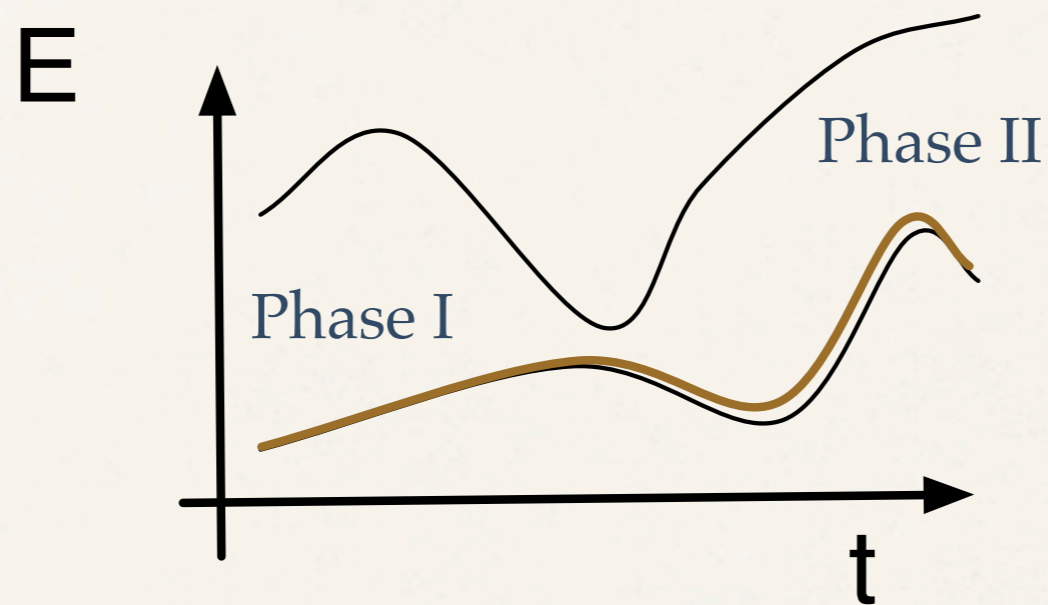
Slow



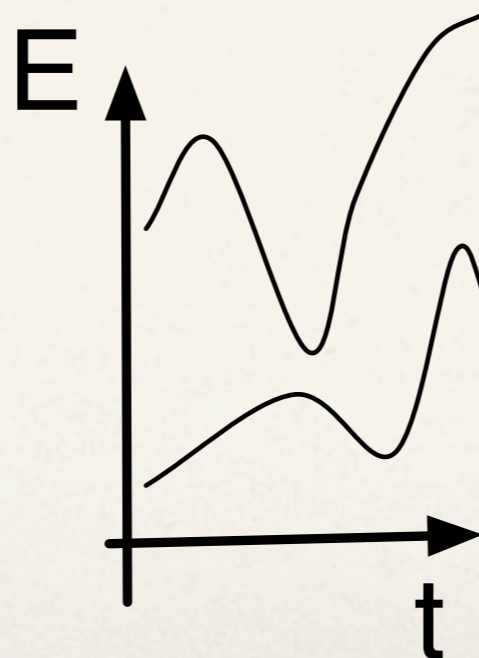
Adiabatic
strategy

Control of QPT dynamics

Slow

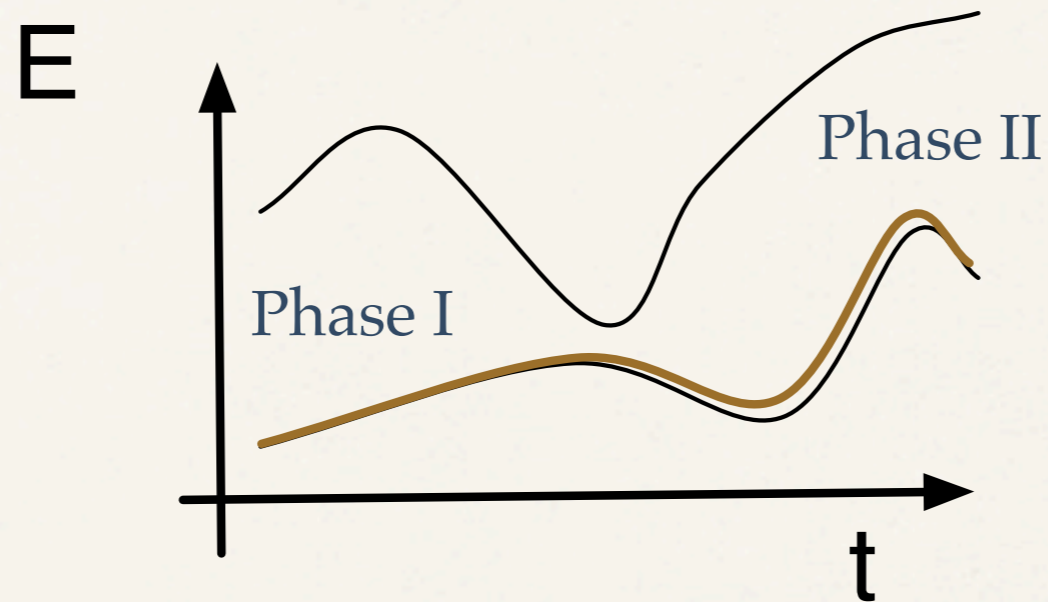


Adiabatic
strategy



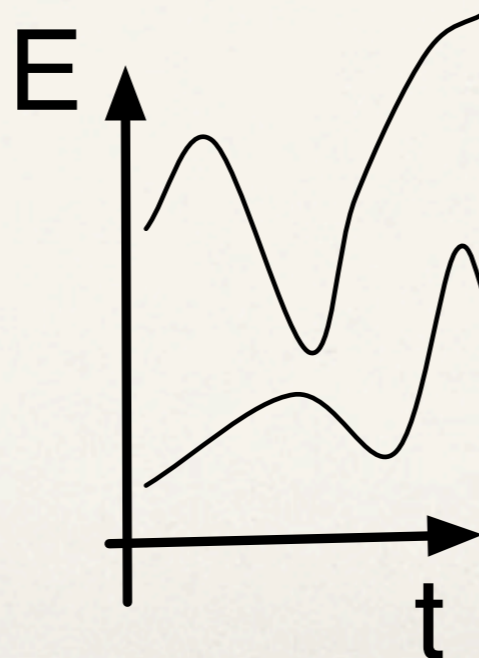
Control of QPT dynamics

Slow



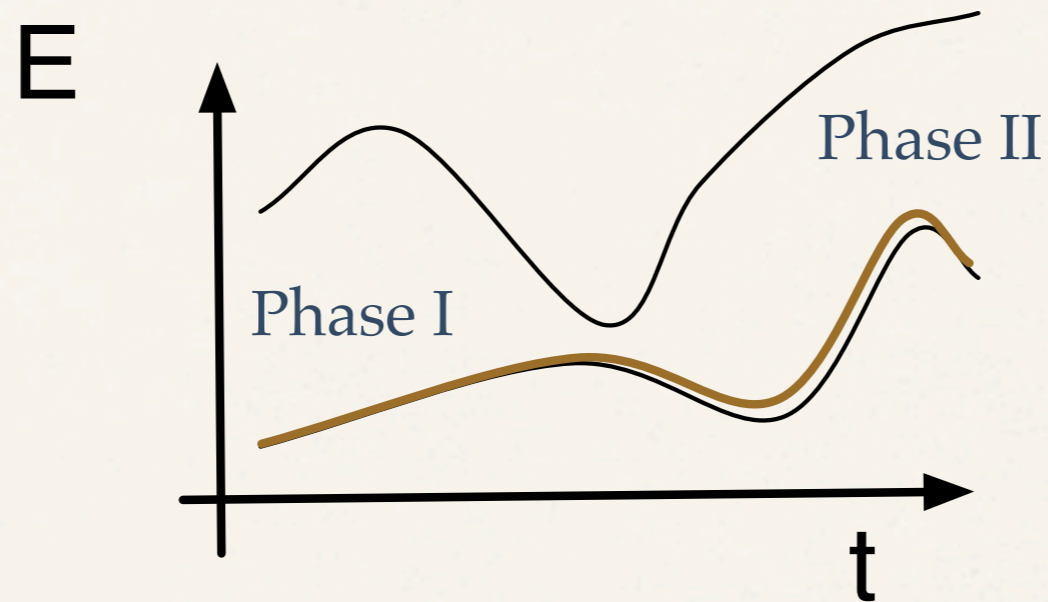
Adiabatic
strategy

Fast



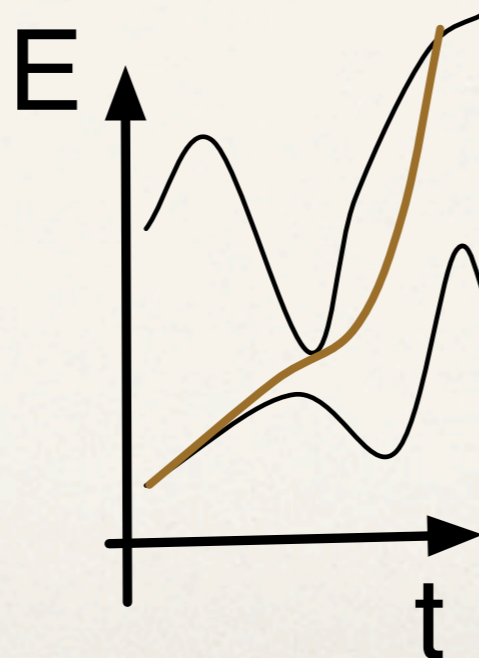
Control of QPT dynamics

Slow



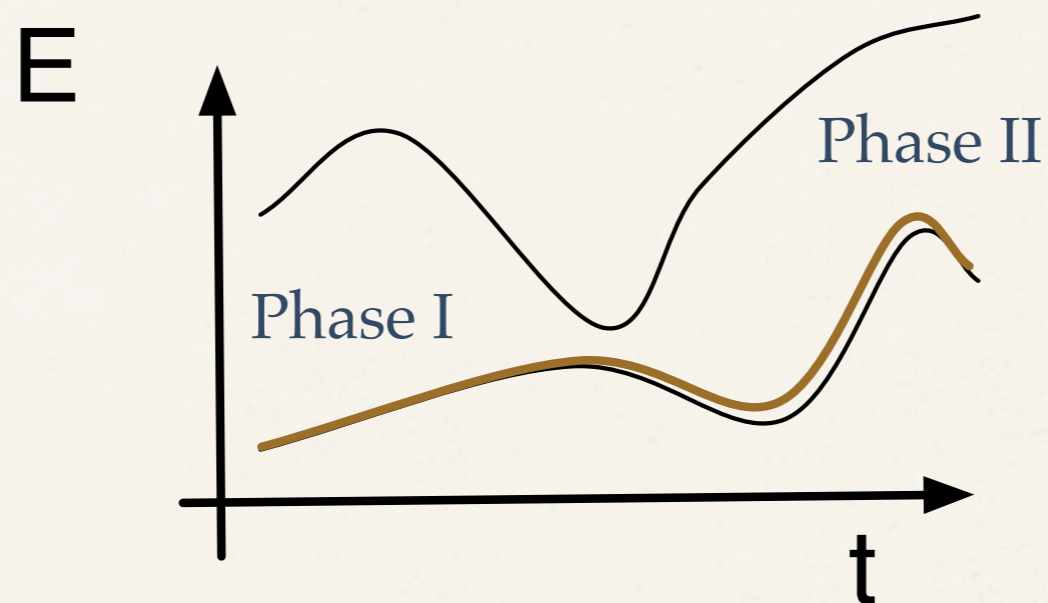
Adiabatic
strategy

Fast



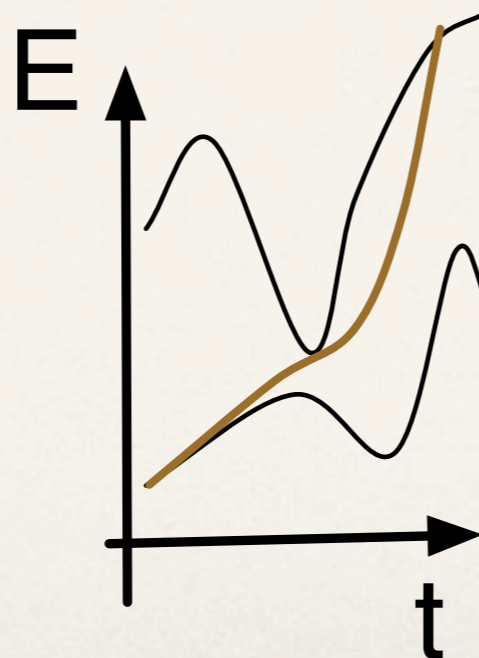
Control of QPT dynamics

Slow



Adiabatic
strategy

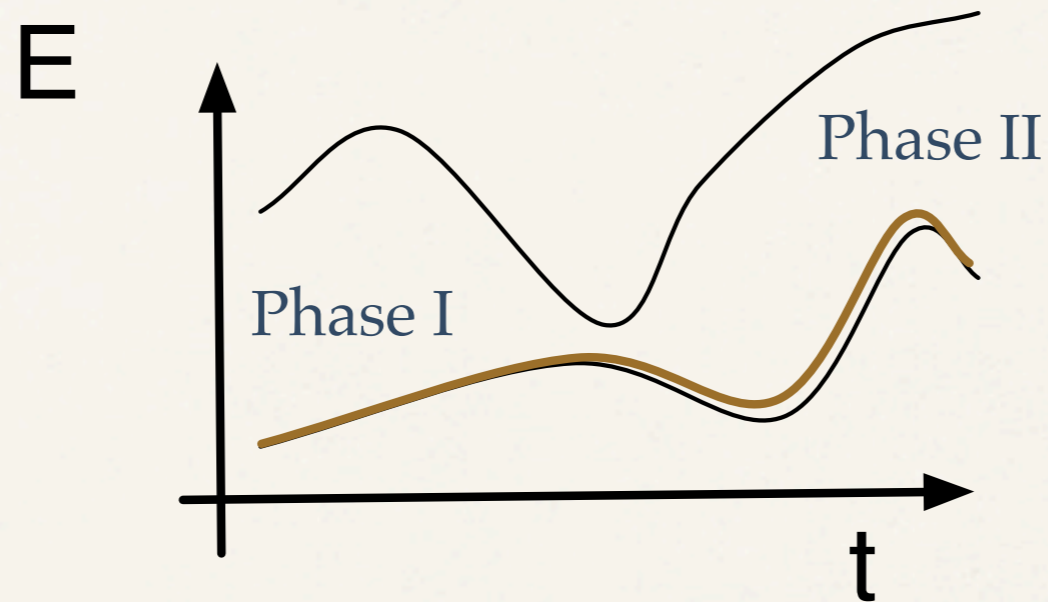
Fast



Optimal
control

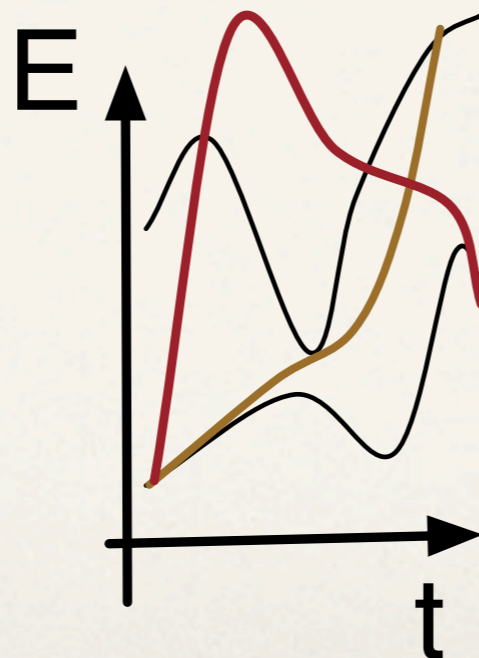
Control of QPT dynamics

Slow



Adiabatic
strategy

Fast



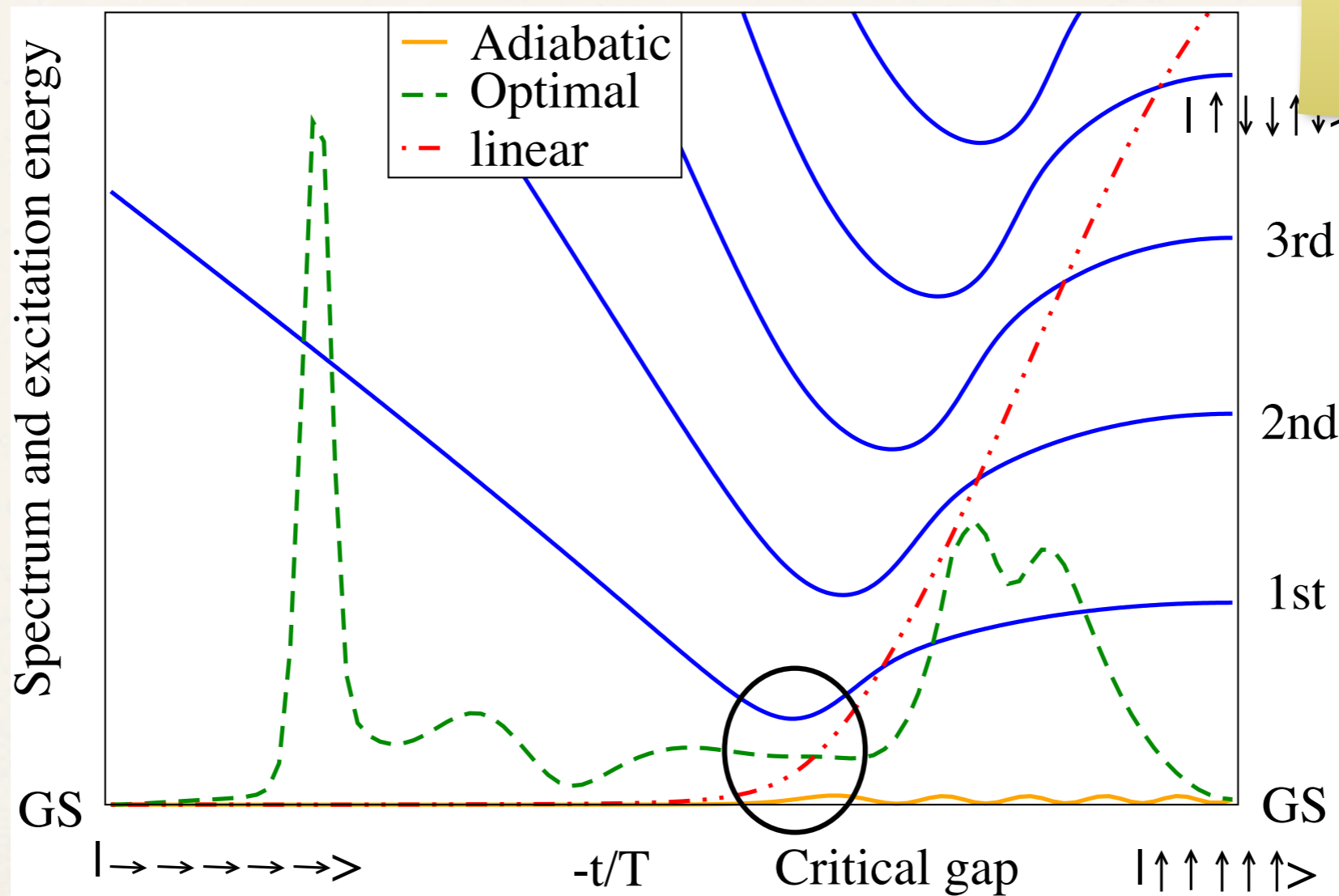
Optimal
control

Optimal QPT crossing

atoms in cavities!

Dicke model + adiabatic elimination

LMG model



$$H = -\frac{1}{N} \sum_{i < j} (\sigma_i^x \sigma_j^x + \gamma \sigma_i^y \sigma_j^y) - \Gamma(t) \sum_i \sigma_i^z$$

Mott-Insulator Superfluid QPT

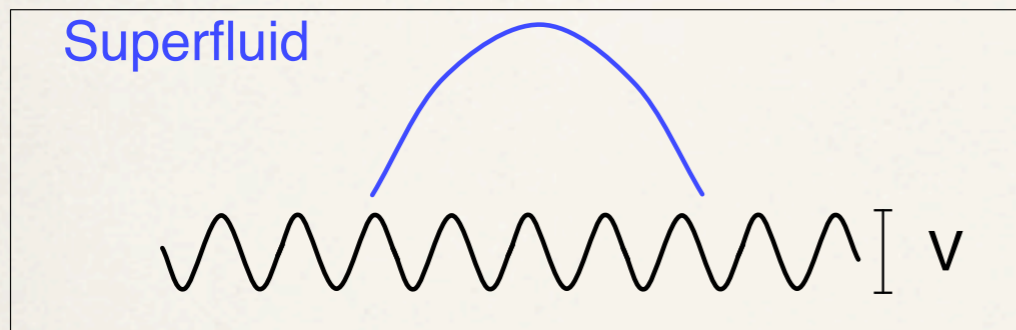
Mott-Insulator Superfluid QPT

$$H = \sum_j \left[-J (b_j^\dagger b_{j+1} + \text{h.c.}) + \Omega \left(j - \frac{N}{2} \right)^2 n_j + \frac{U}{2} (n_j^2 - n_j) \right]$$

J Hopping
 U Onsite energy
 Ω Trapping

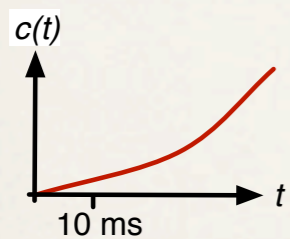
Mott-Insulator Superfluid QPT

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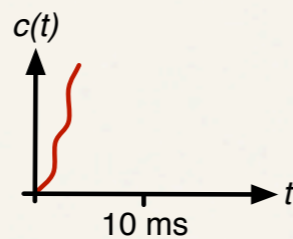


$$J/U \gg 0.1$$

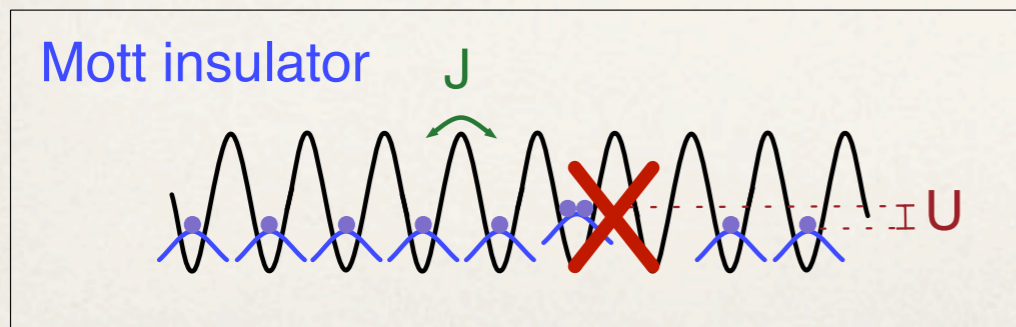
Adiabatic



Antiadiabatic



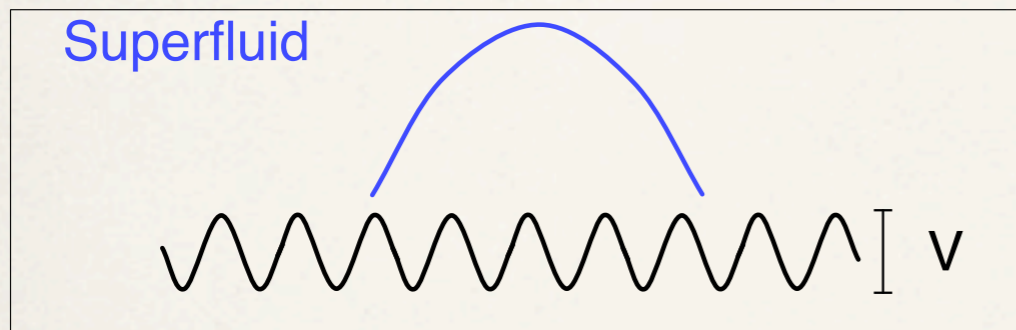
J Hopping
 U Onsite energy
 Ω Trapping



$$J/U \ll 0.1$$

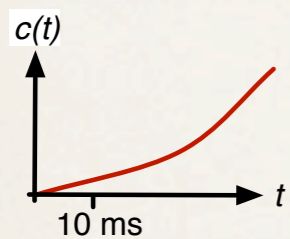
Mott-Insulator Superfluid QPT

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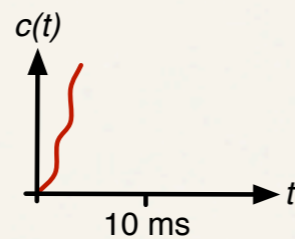


$$J/U \gg 0.1$$

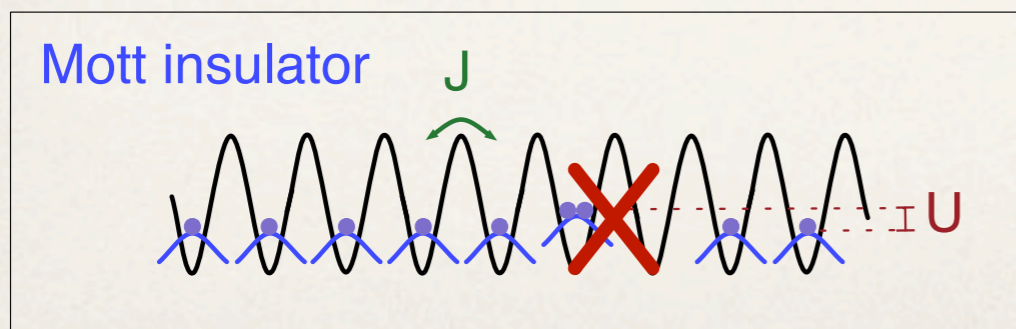
Adiabatic



Antiadiabatic



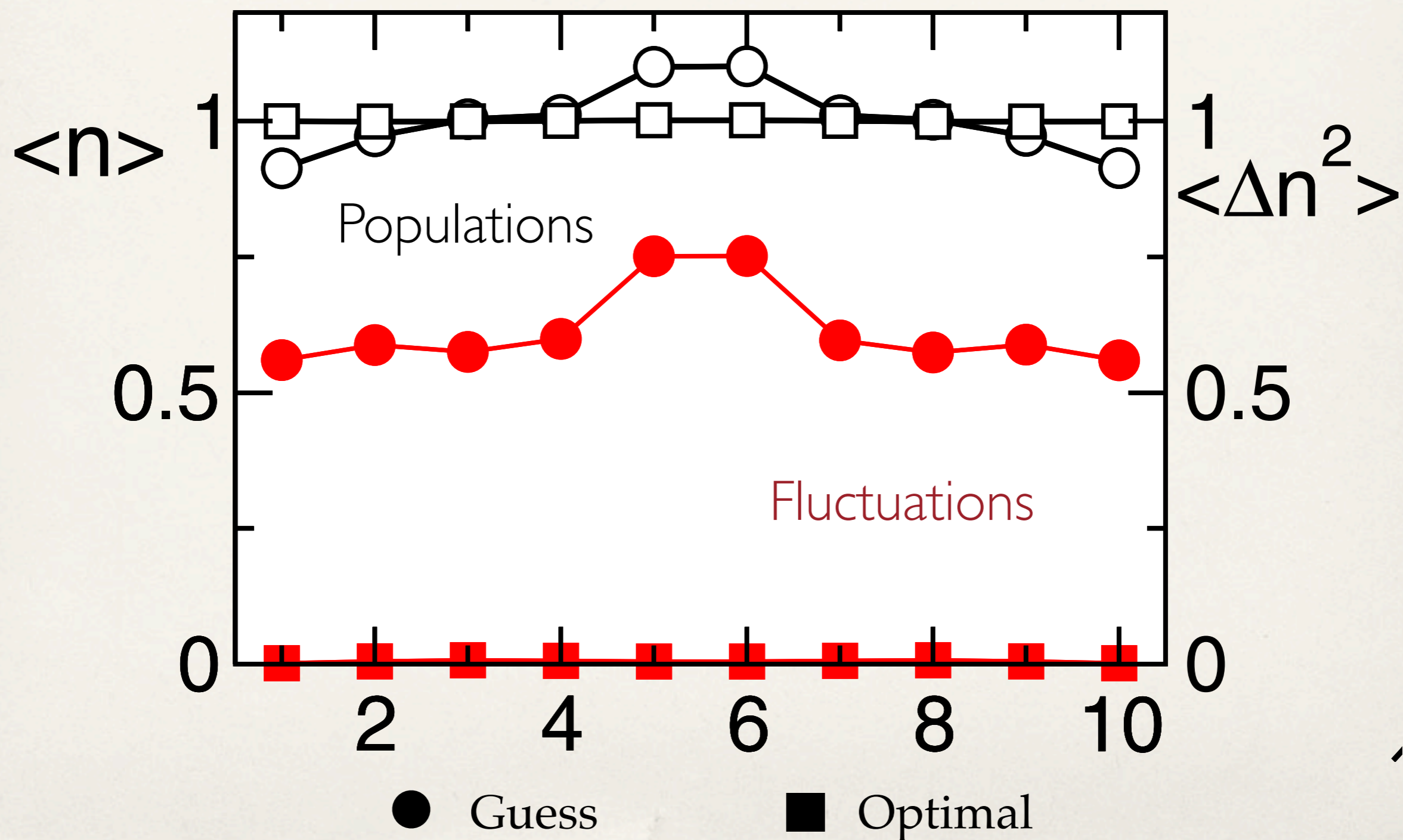
J Hopping
 U Onsite energy
 Ω Trapping



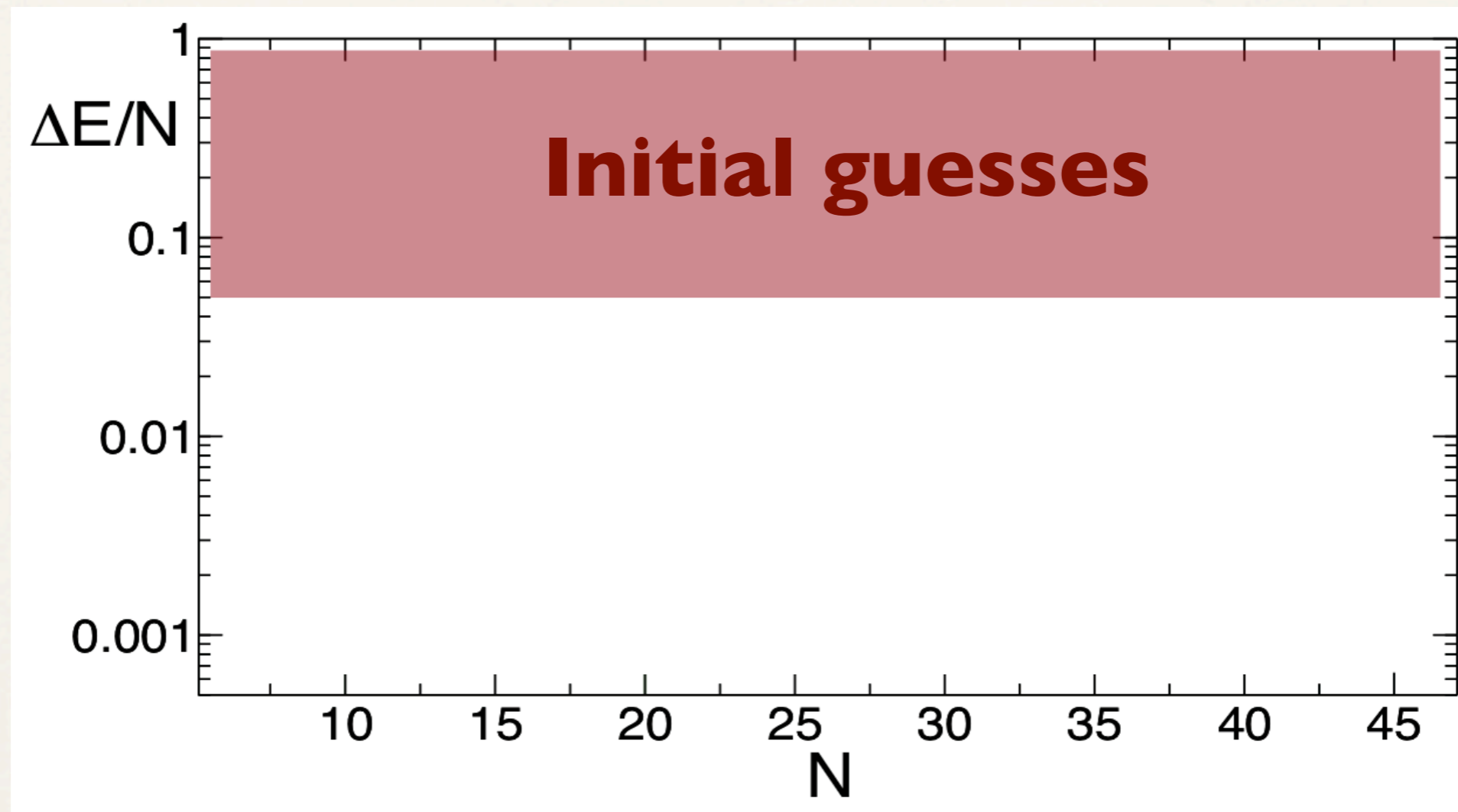
$$J/U \ll 0.1$$

M. Greiner, O. Mandel, T. Esslinger, T.W. Hansch and I. Bloch, Nature 415, 39 (2002).

CRAAB Optimized dynamics

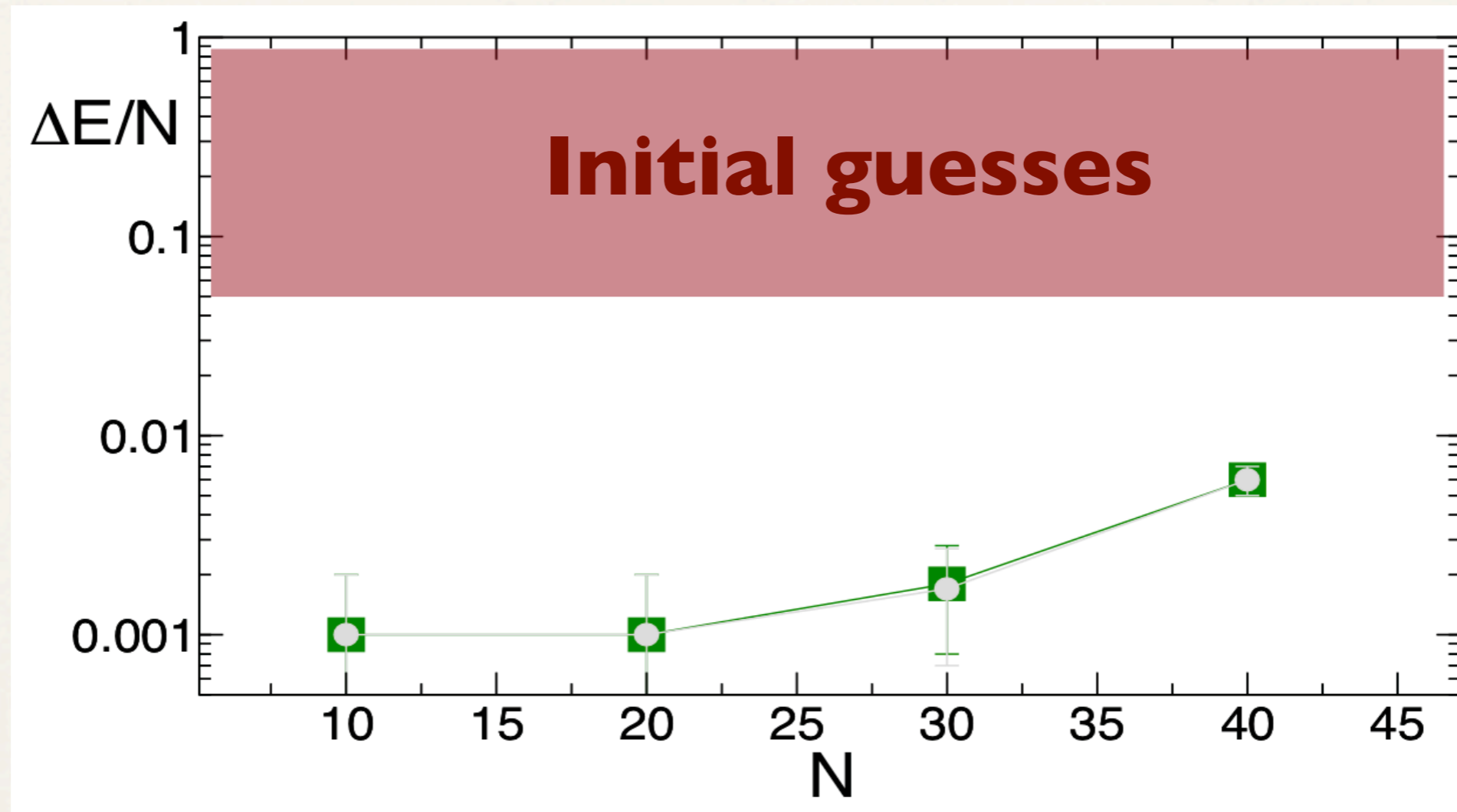


Residual density of defects



$T = 3\text{ms}$

Residual density of defects



$T = 3\text{ms}$

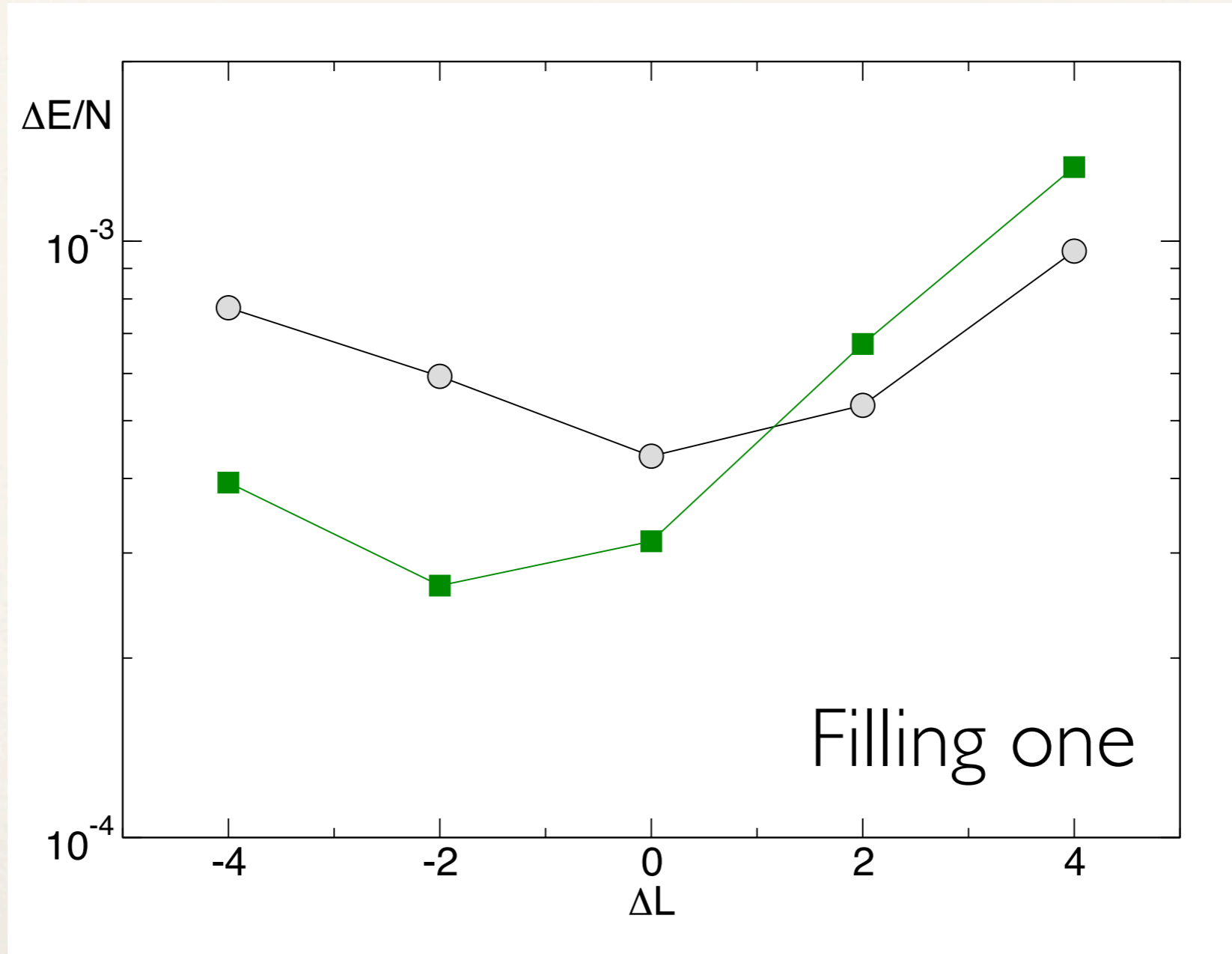
Homogeneous
system

Trapping potential
T. Esslinger group
PRL (2004)

P. Doria, T. Calarco, SM Phys. Rev. Lett. 106, 190501 (2011)

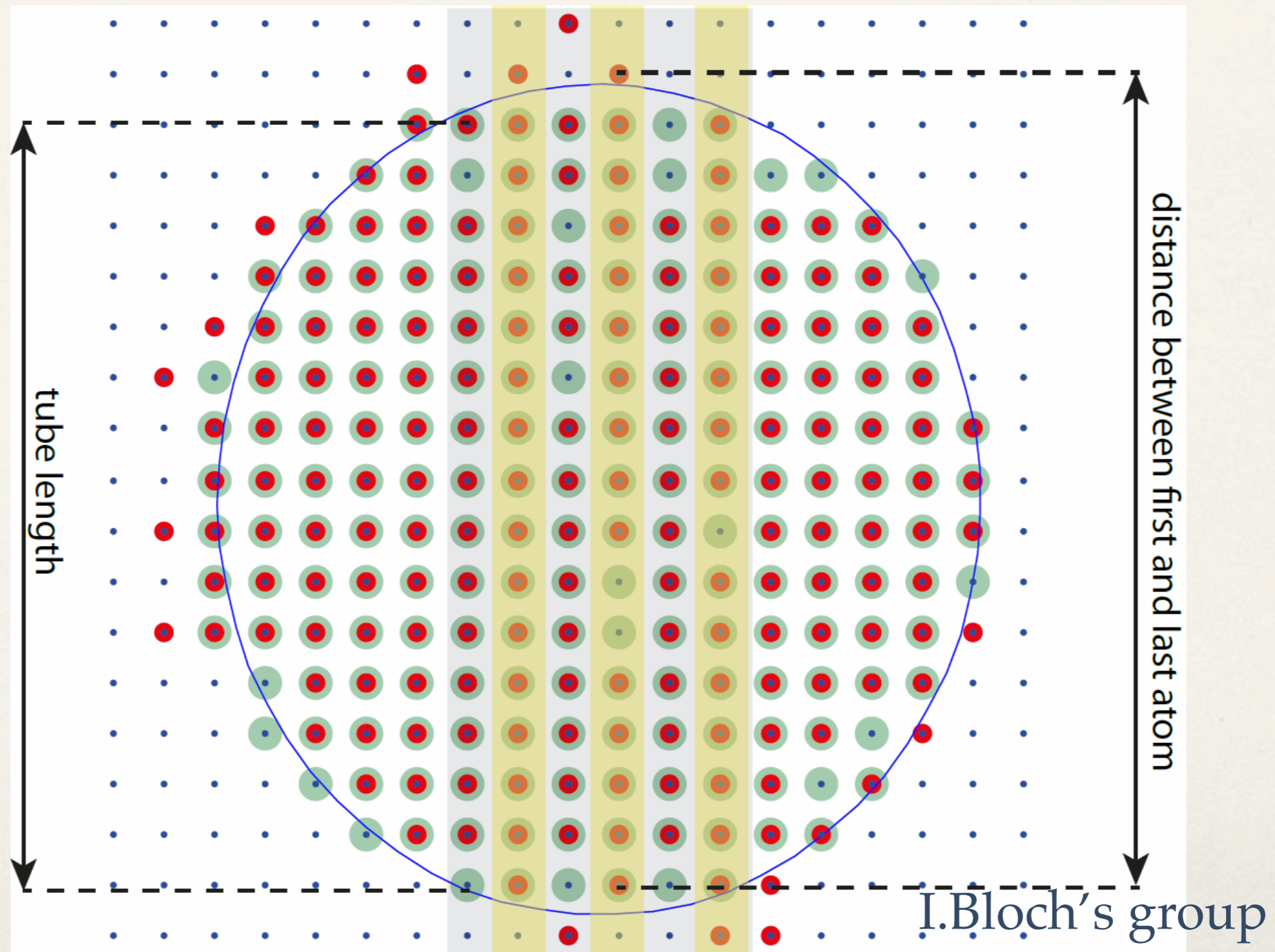
Atom number fluctuations

Optimal pulse
for $L=20$

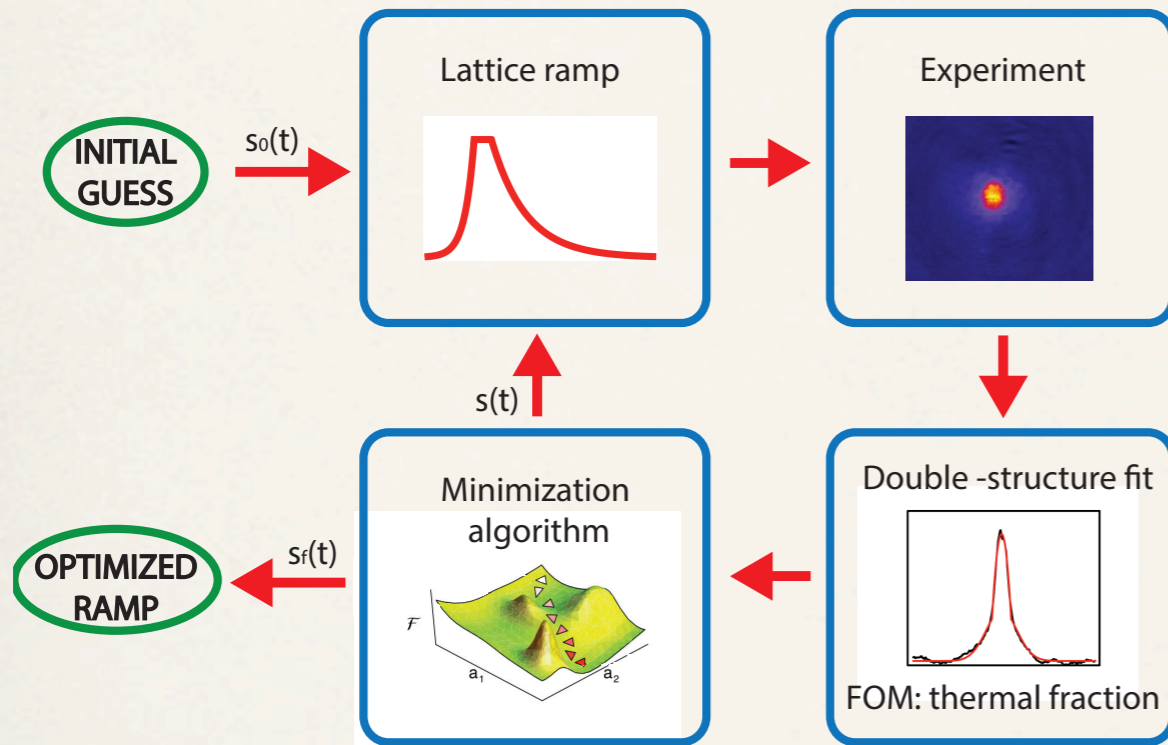


Open loop optimization

Open loop optimization



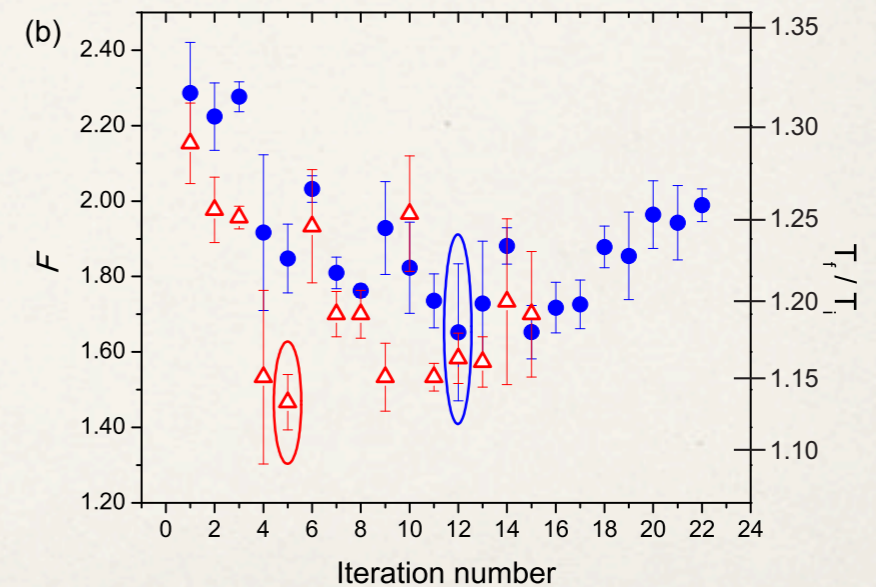
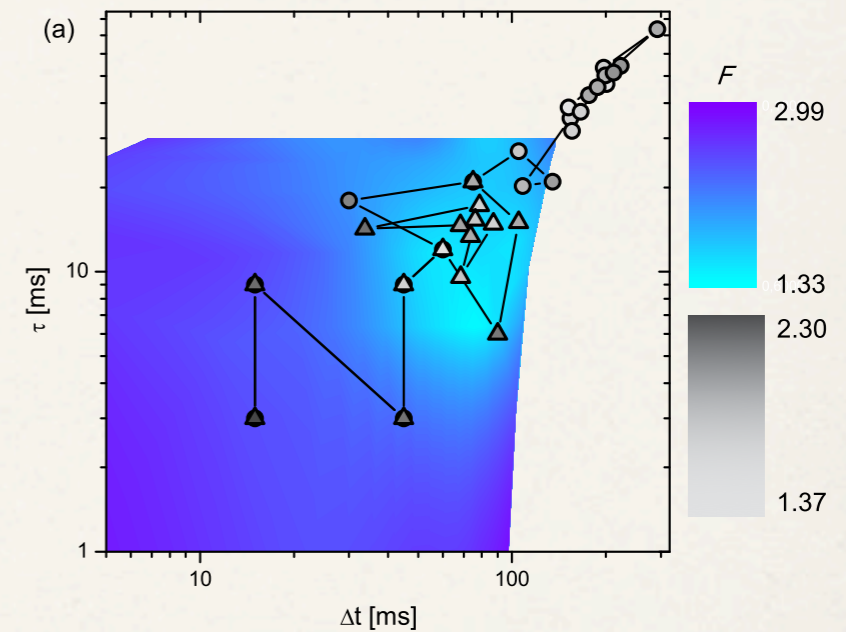
Closed loop optimization



3D-1D crossover and QPT

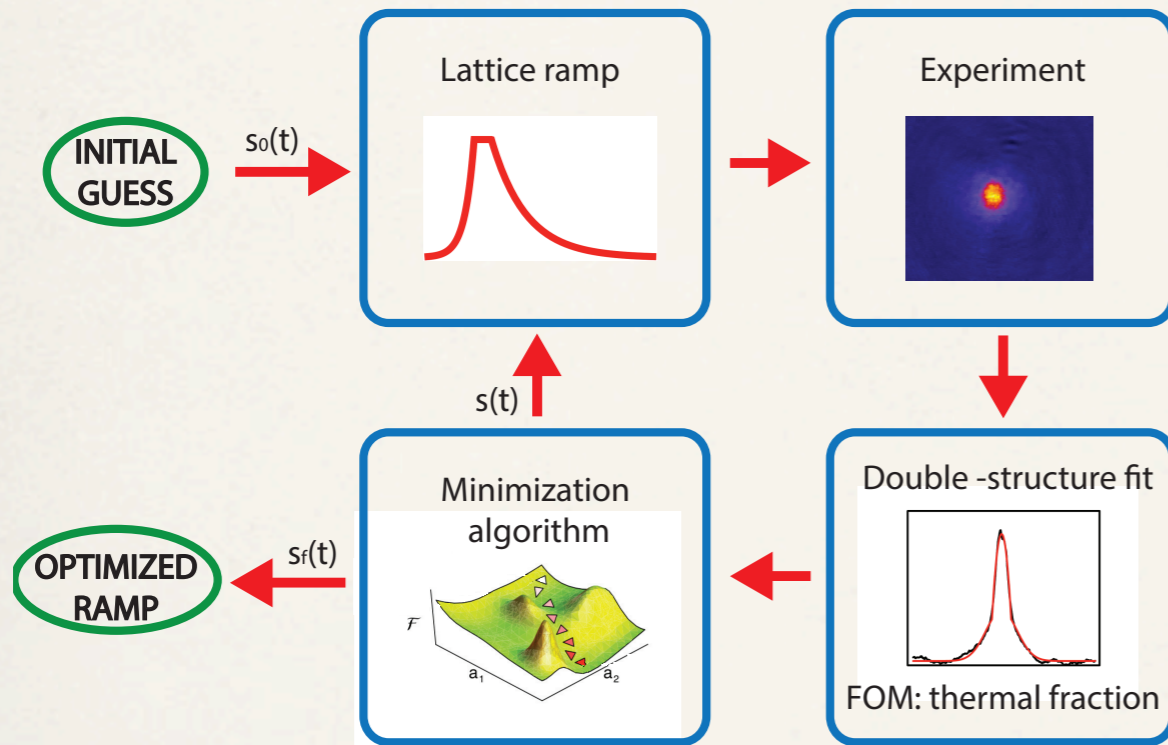
$$T_{opt} \sim T_{ad}/3$$

$$FOM_{opt} \sim 0.9 FOM_{ad}$$



Run	Δt_{opt}	τ_{opt}	F_{uncorr}	Best F_{opt}
1	154 ms	35 ms	2.30 ± 0.03	1.73 ± 0.02
2	45 ms	9 ms	2.30 ± 0.03	1.40 ± 0.06

Closed loop optimization

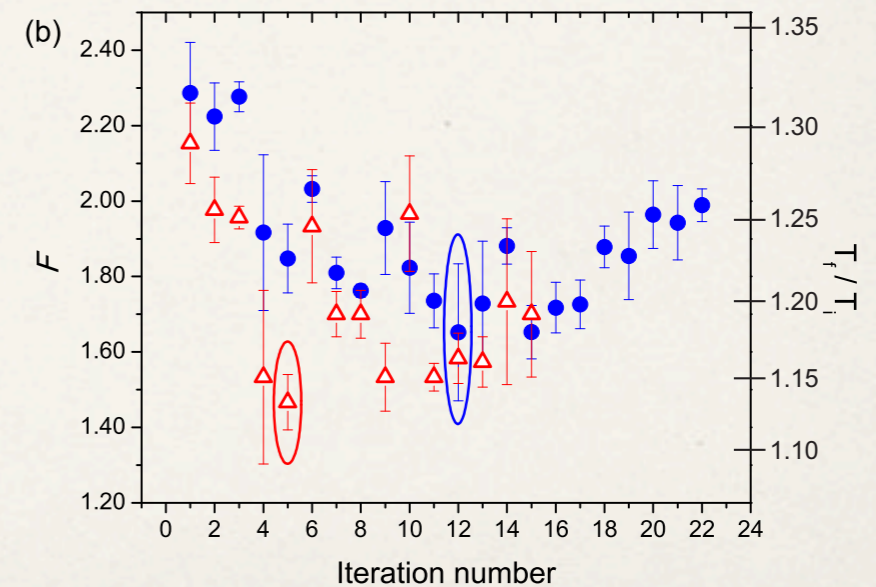
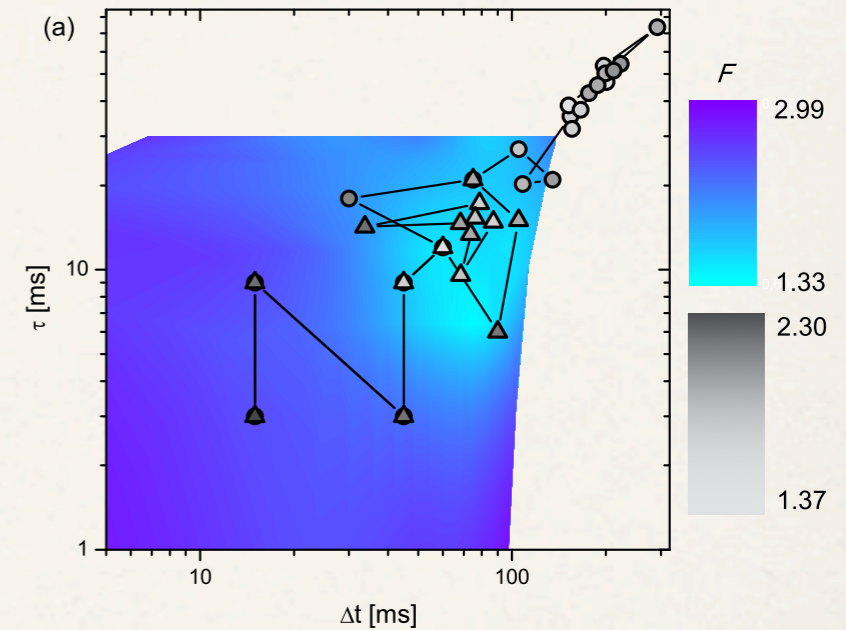


3D-1D crossover and QPT

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S. Rosi, et. al. in preparation



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Paradigm shift

Paradigm shift

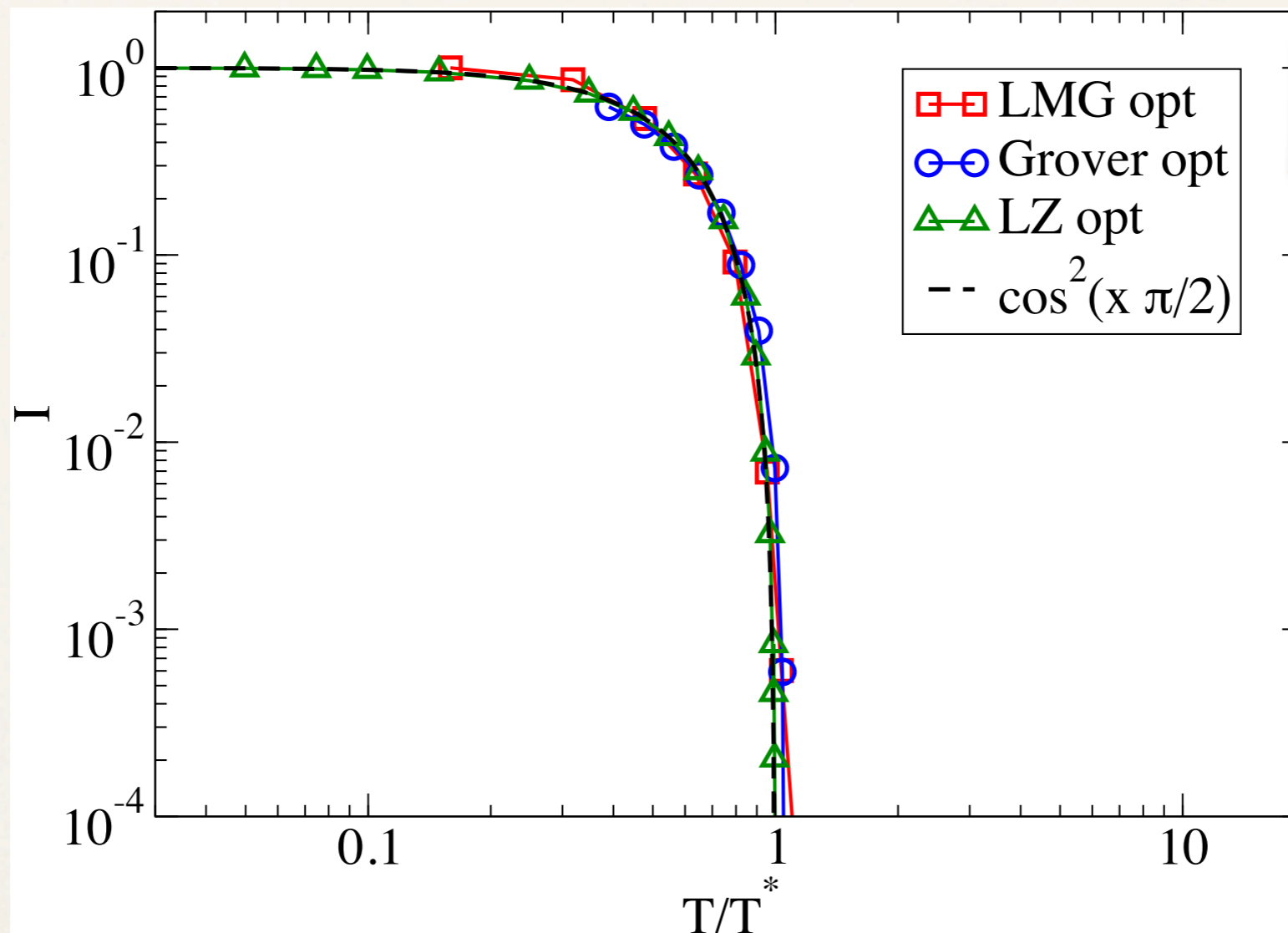
How do we control MBQS?

Paradigm shift

Under which conditions
can we control MBQS?

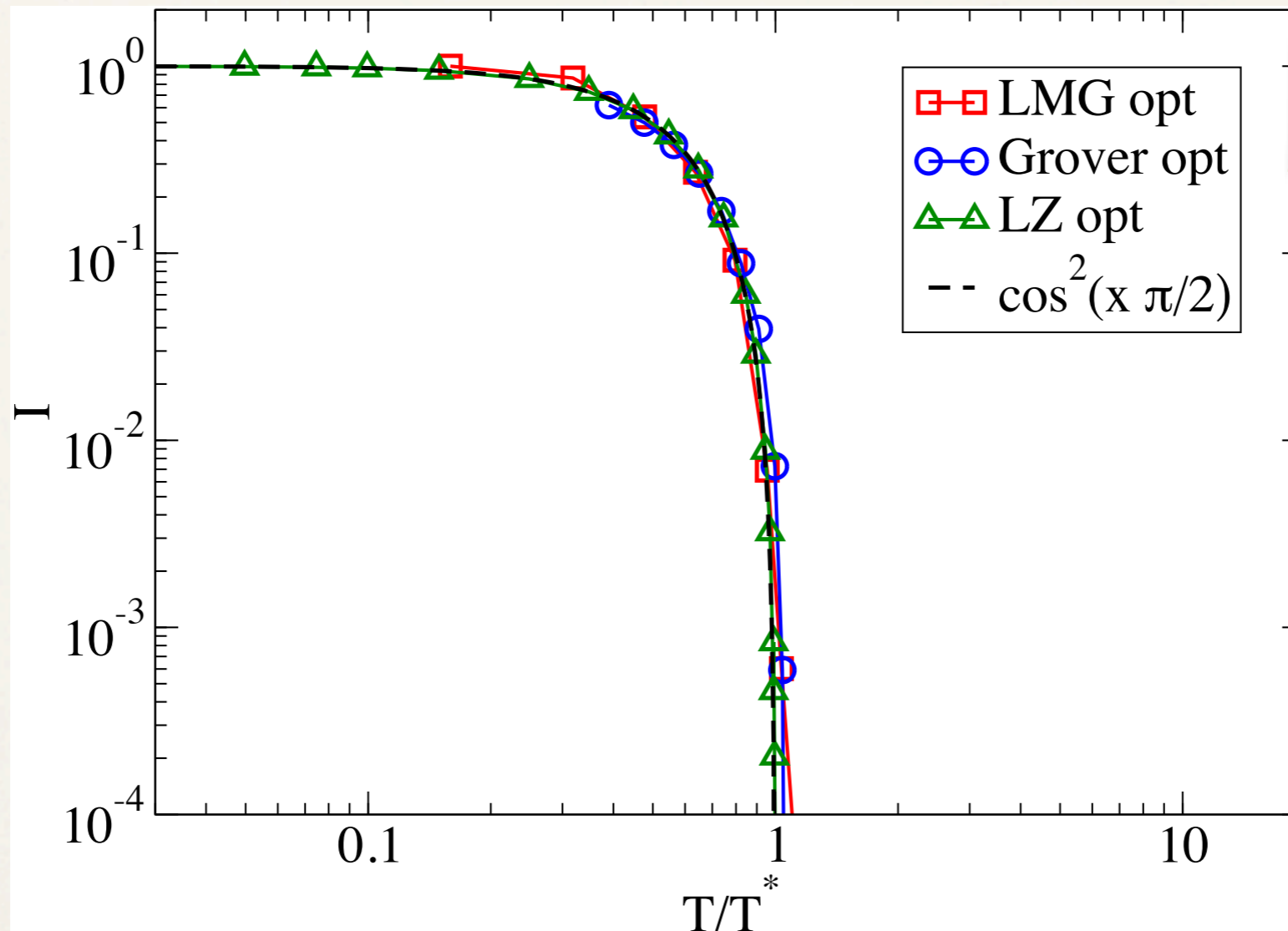
Quantum speed limit

pfeiffer 1993
battacharrya 1983
margolus and levitin
1998
alberto carlini



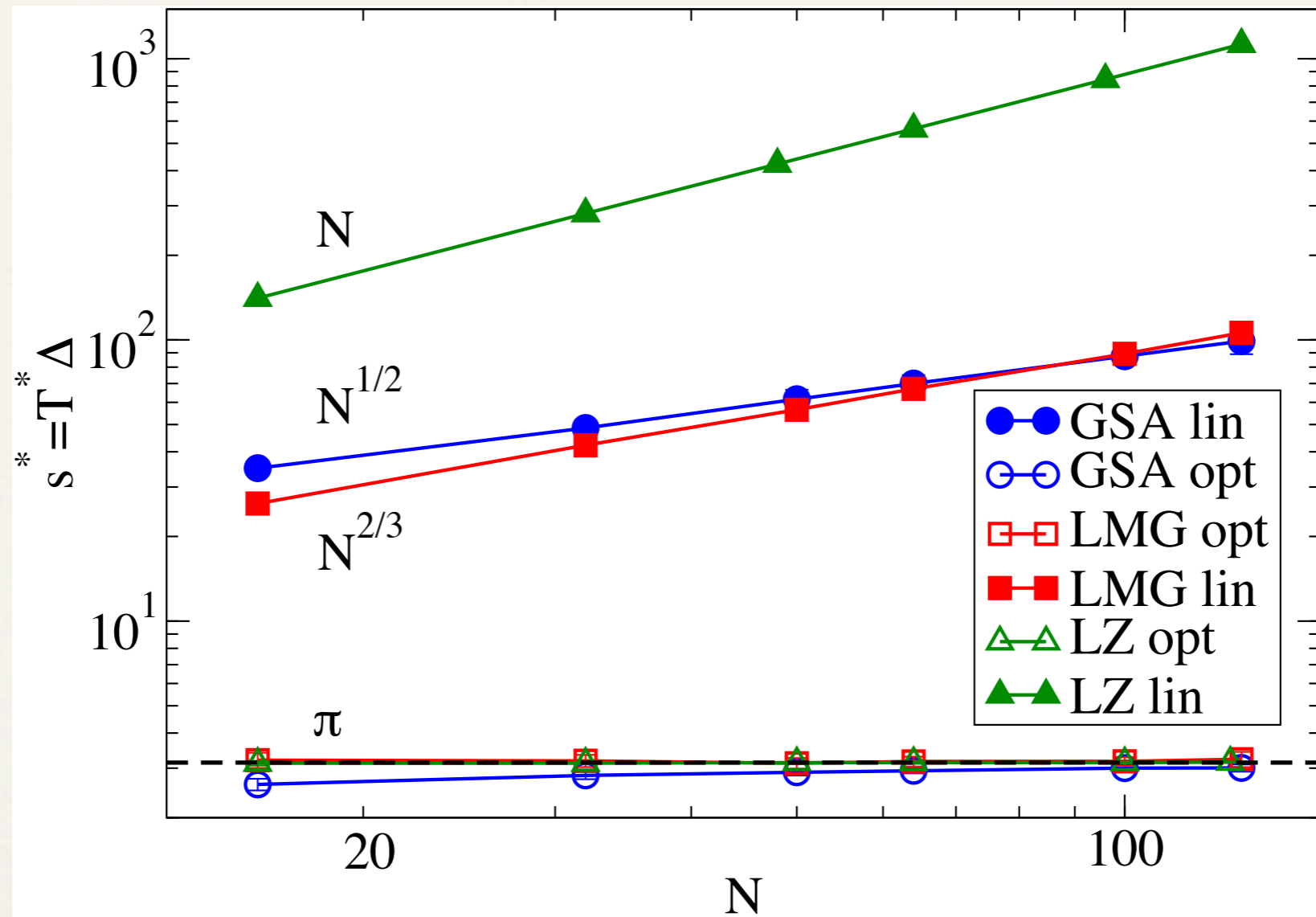
Quantum speed limit

pfeiffer 1993
battacharrya 1983
margolus and levitin
1998
alberto carlini



see also T. Caneva, M. Murphy, T. Calarco, R. Fazio, SM, V. Giovannetti, and G. E. Santoro, Phys. Rev. Lett. 103, 240501 (2009).

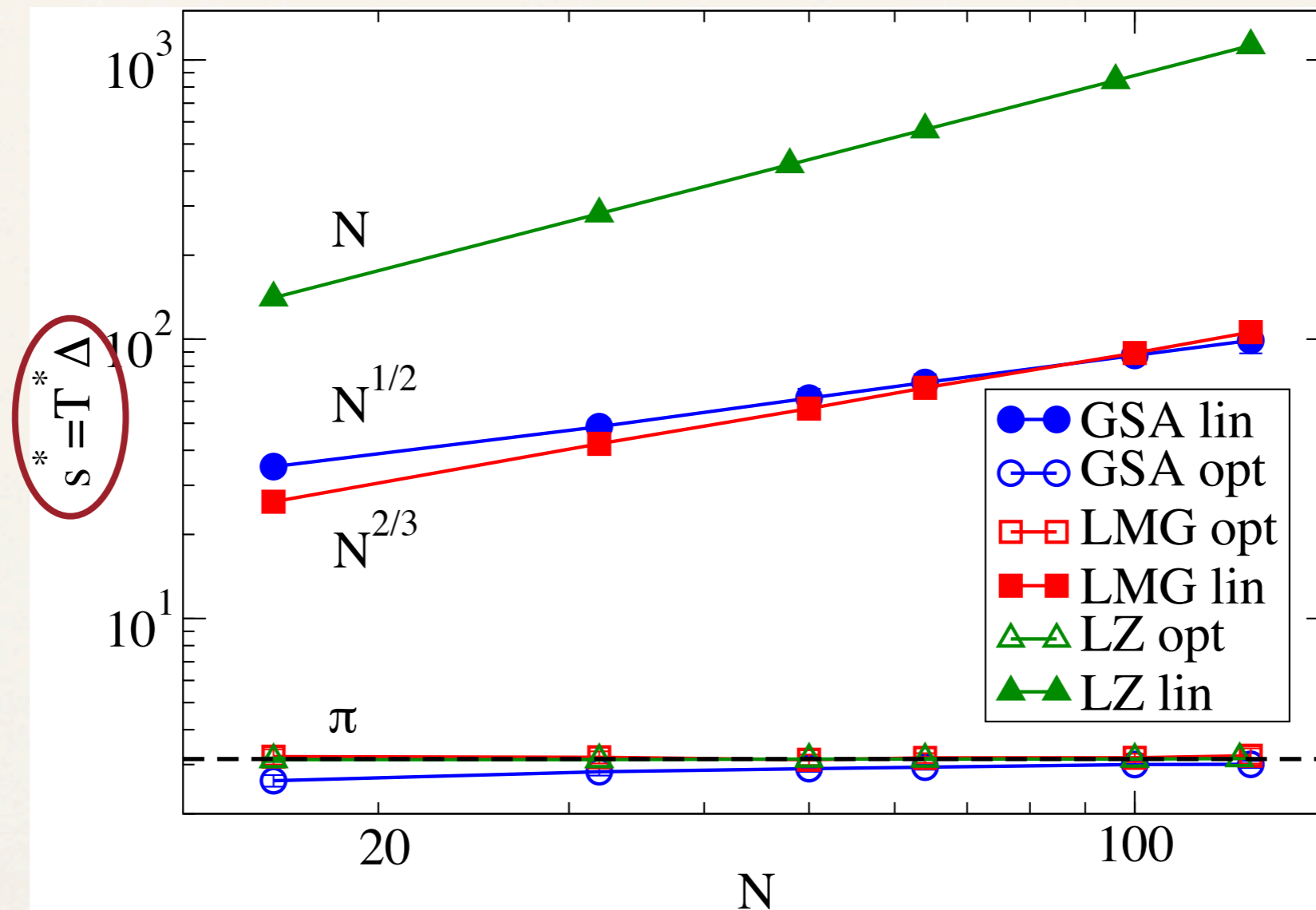
Optimal action



Optimal
scaling

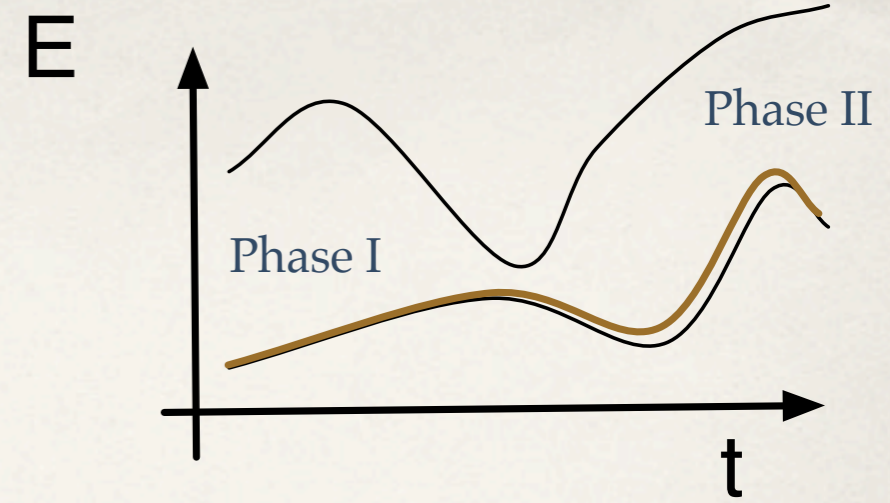
Optimal action

Optimal
action
QSL



Optimal
scaling

QPT crossing scenario



$$T \ll \Delta^{-1}$$

$$T \sim \Delta^{-1}$$

$$T \gg \Delta^{-1}$$

$$I \sim O(1)$$

$$I(s \gg 1) \rightarrow 0$$

Linear

s

π

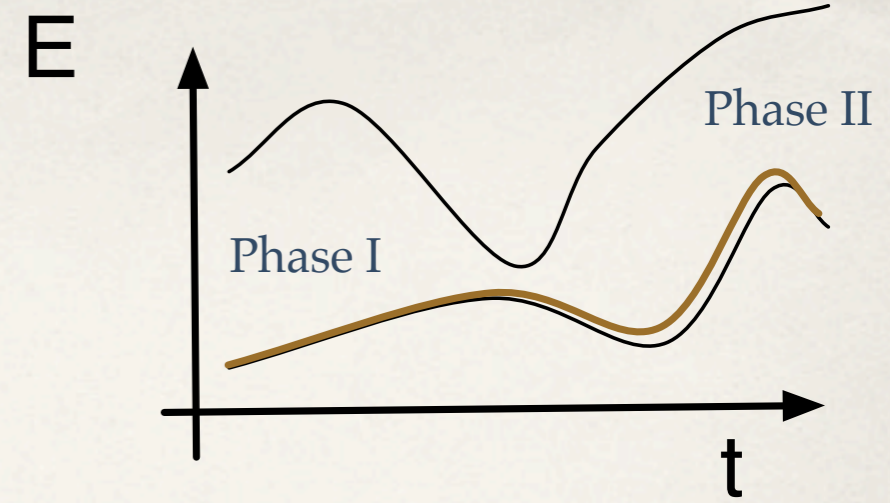
∞

Kibble Zurek

QSL

Adiabatic

QPT crossing scenario



$$T \ll \Delta^{-1}$$

$$T \sim \Delta^{-1}$$

$$T \gg \Delta^{-1}$$

$$I \sim O(1)$$

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Linear

s



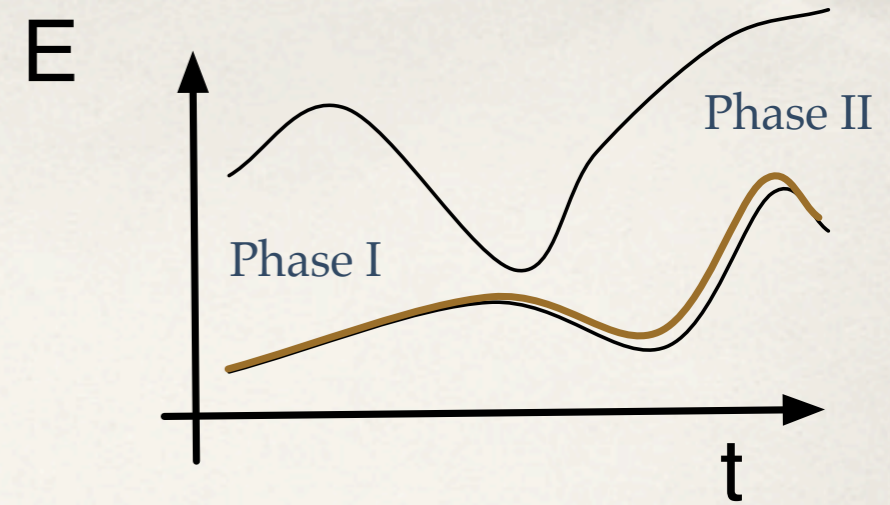
Optimal

Kibble Zurek

QSL

Adiabatic

QPT crossing scenario



$$T \ll \Delta^{-1}$$

$$T \sim \Delta^{-1}$$

$$T \gg \Delta^{-1}$$

$$I \sim O(1)$$

$$I(s \gg 1) \rightarrow 0$$

$$I = \cos^2(s/2)$$

$$I = 0$$

Linear

s

π

∞

Optimal

s

π

∞

Kibble Zurek

QSL

Adiabatic

T. Caneva, T. Calarco, R. Fazio, G. E. Santoro, and SM Phys. Rev. A 84, 012312 (2011)

New questions

time 15 min



New questions

How do we control MBQS?

time 15 min

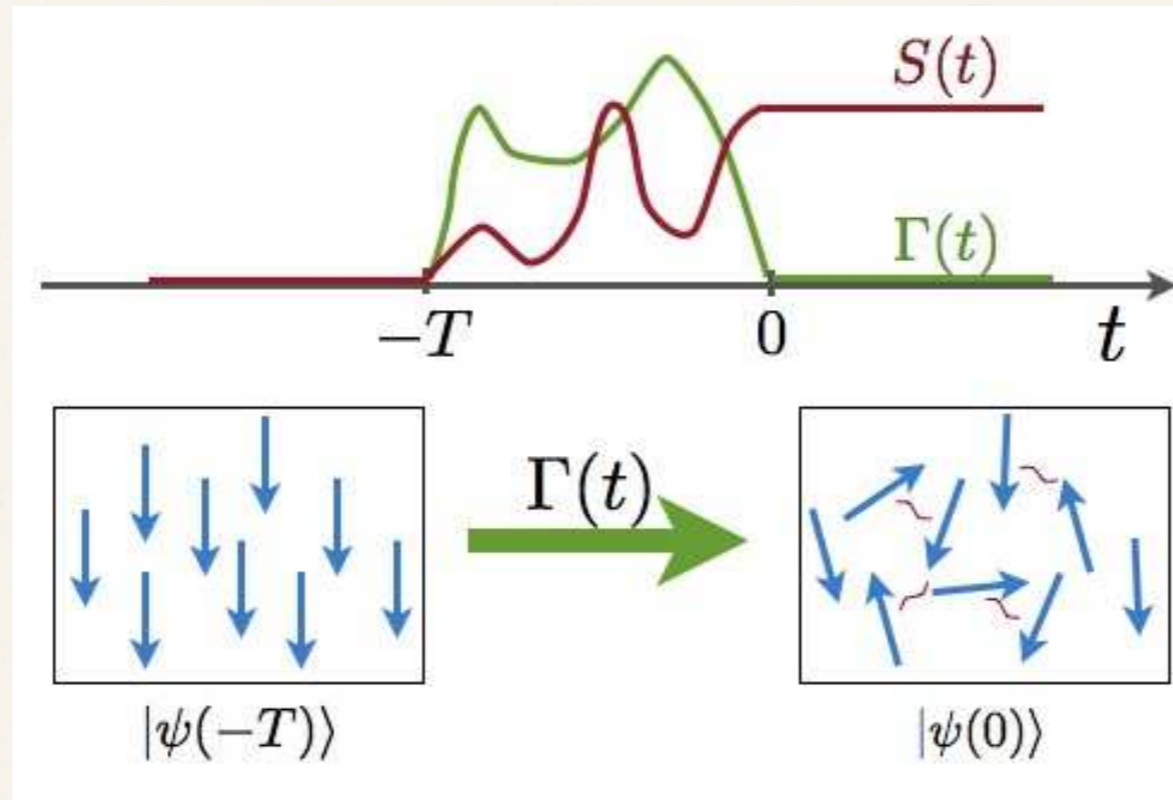


New questions

time 15 min

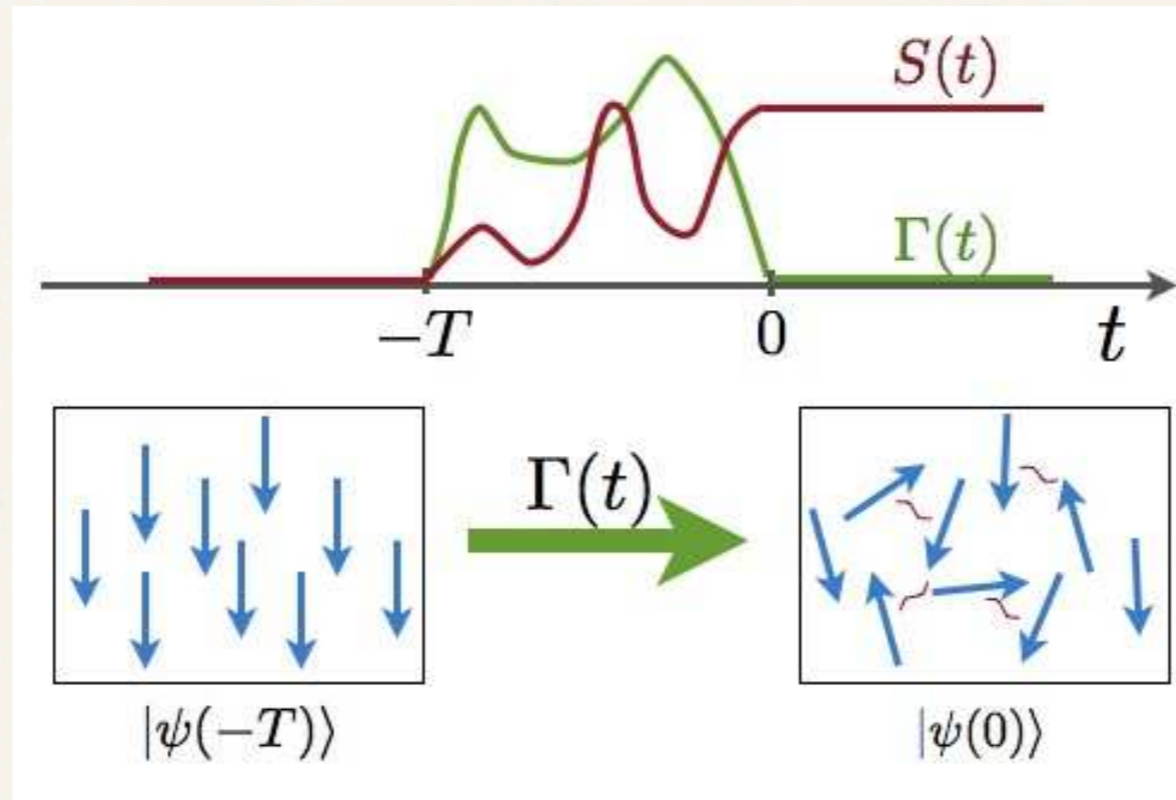
Is there something “new”
we can learn / achieve / gain
exploiting the control MBQS?

Entanglement Storage Units



inset:
 T VS noise intensity

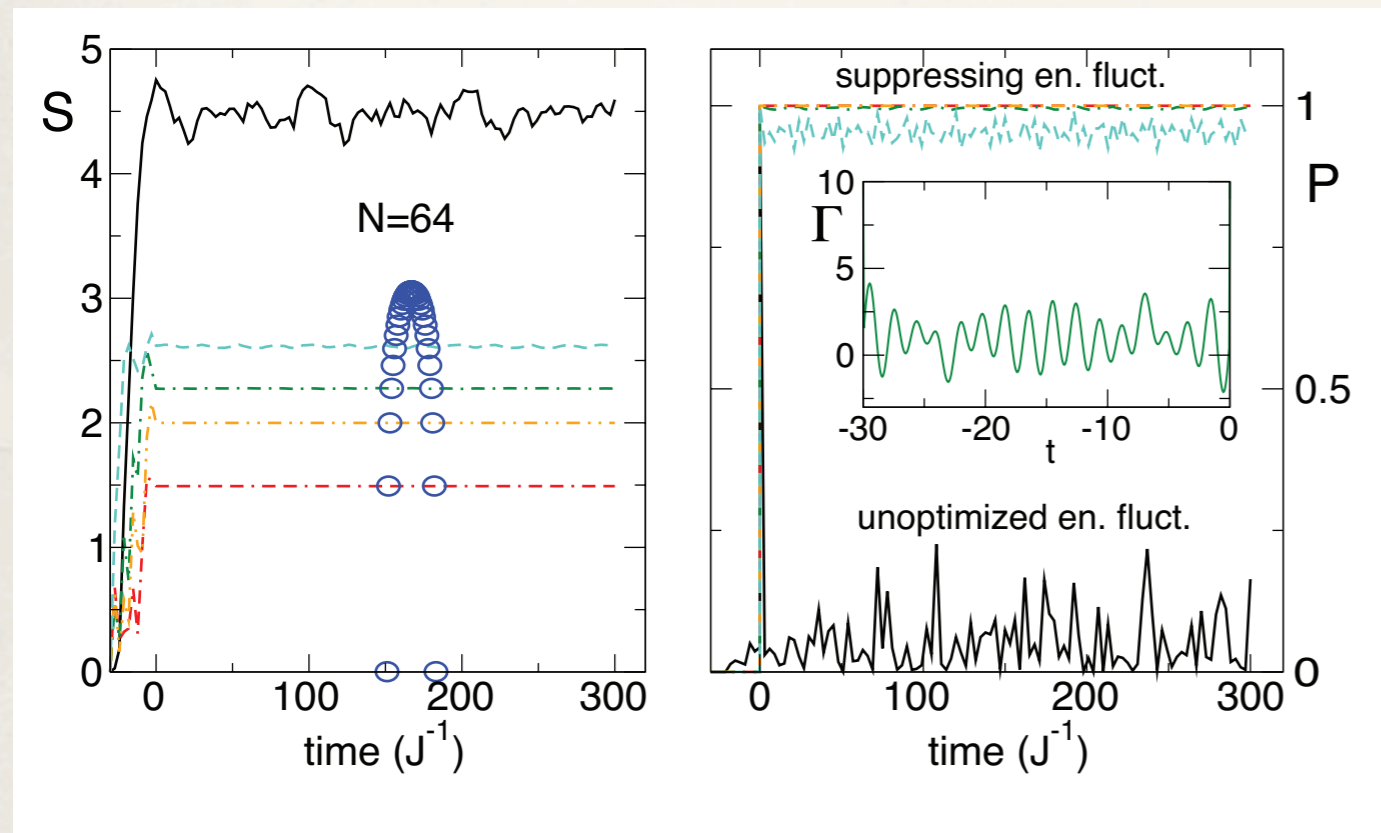
Entanglement Storage Units



inset:
 T VS noise intensity

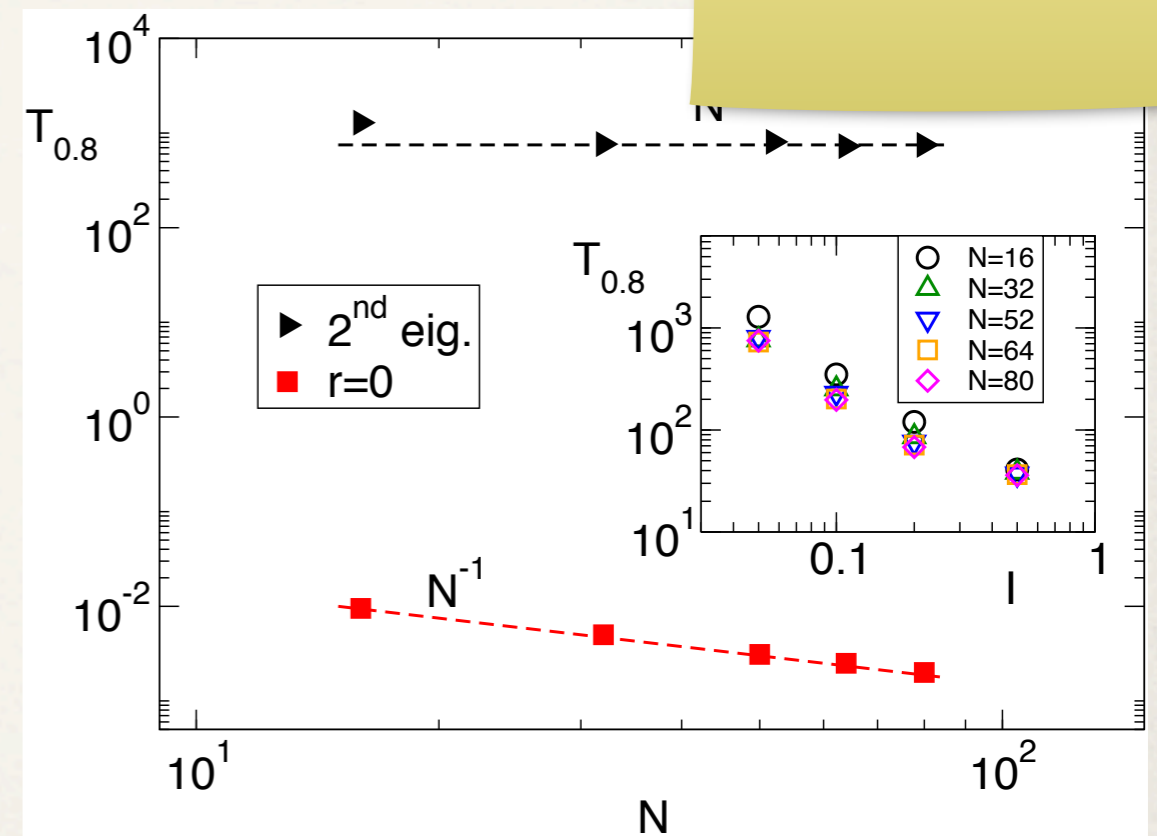
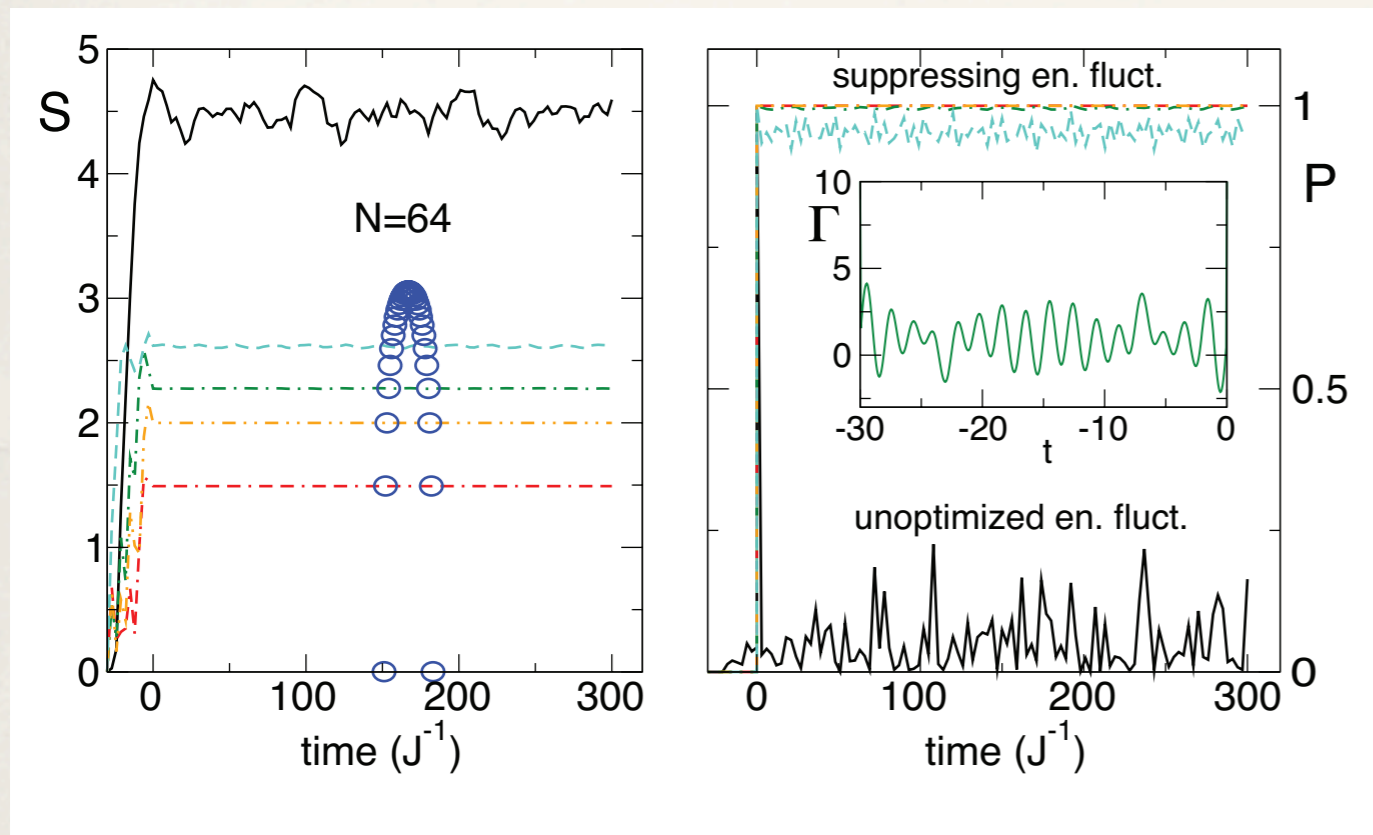
Entanglement Storage Units

inset:
T VS noise intensity



T. Caneva, T. Calarco, SM, New J. Phys. 14 093041 (2012)

Entanglement Storage Units

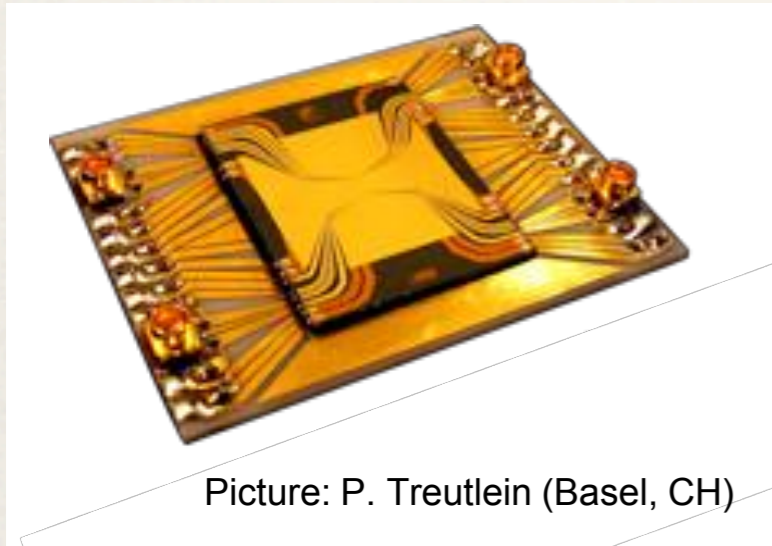


inset:
T VS noise intensity

T. Caneva, T. Calarco, SM, New J. Phys. 14 093041 (2012)

Atom chip experiments at QSL

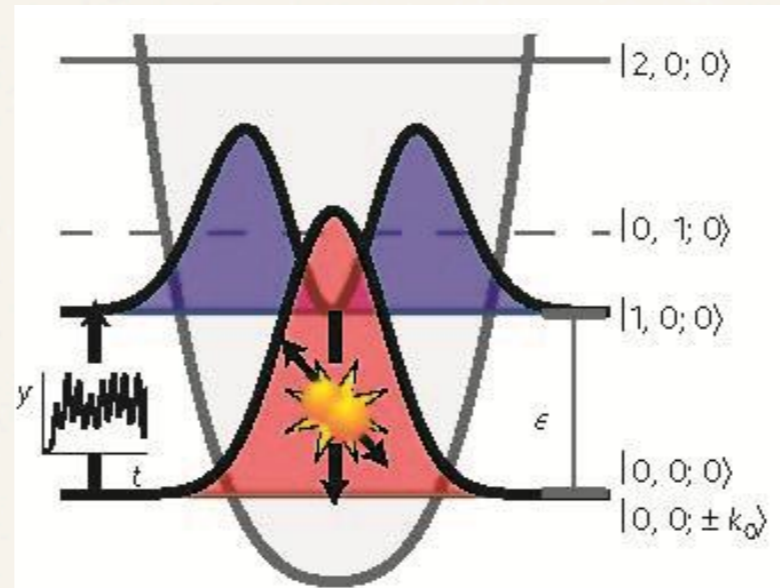
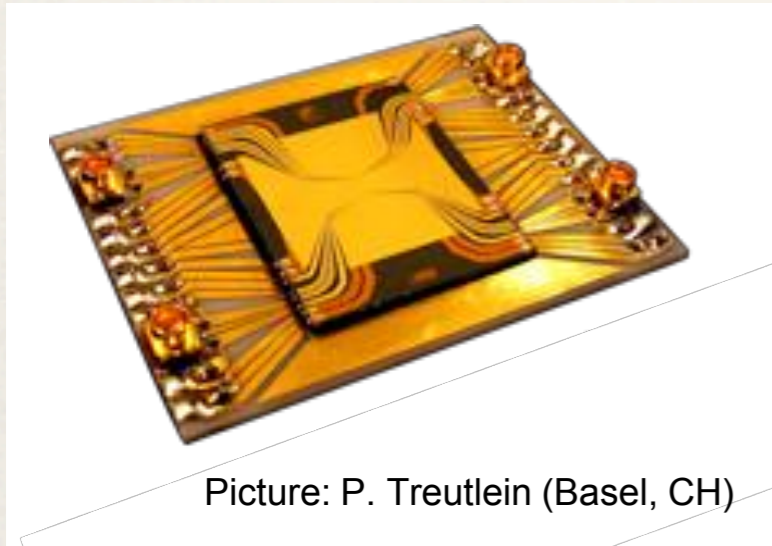
see also R. Büker et. al. Nat. Phys. 2011



Picture: P. Treutlein (Basel, CH)

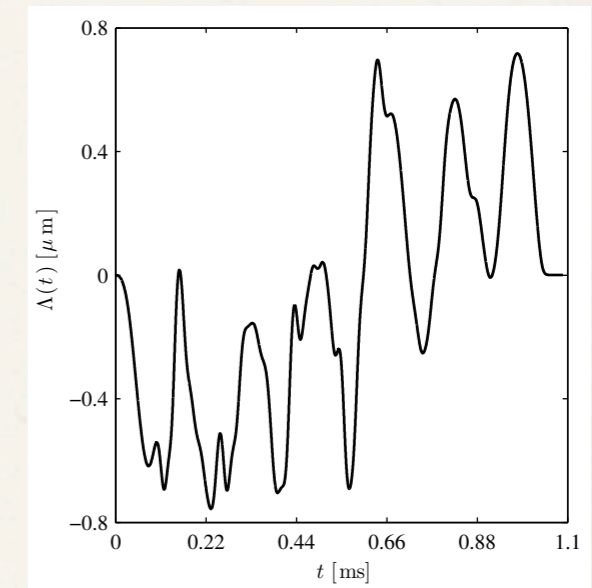
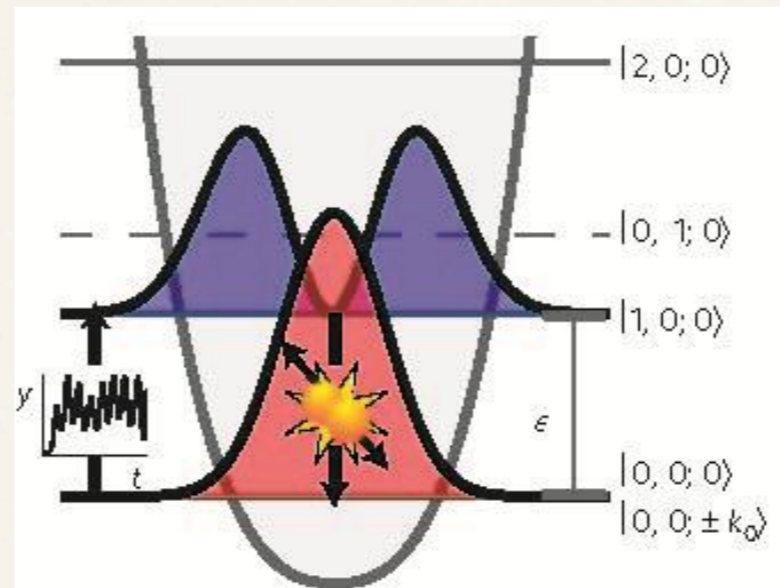
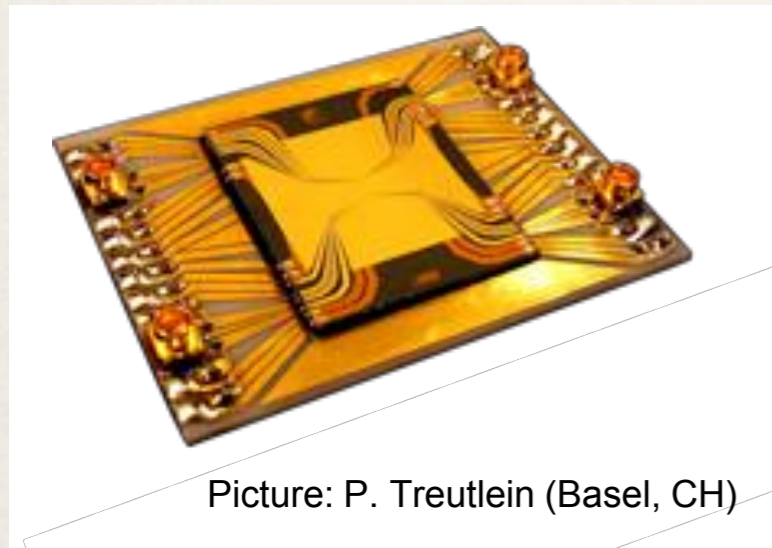
Atom chip experiments at QSL

see also R. Büker et. al. Nat. Phys. 2011



Atom chip experiments at QSL

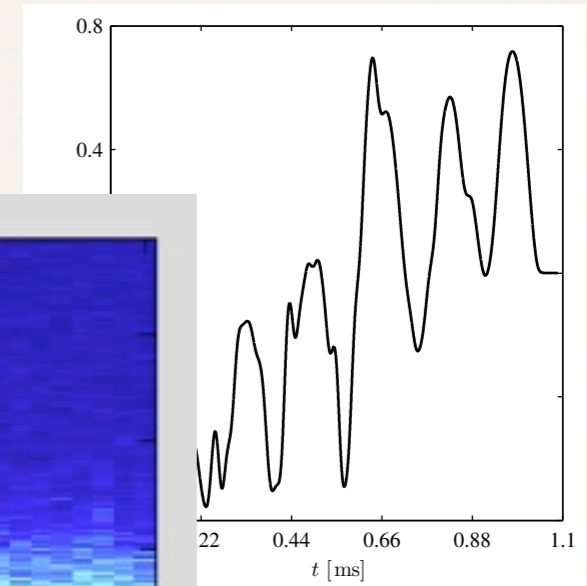
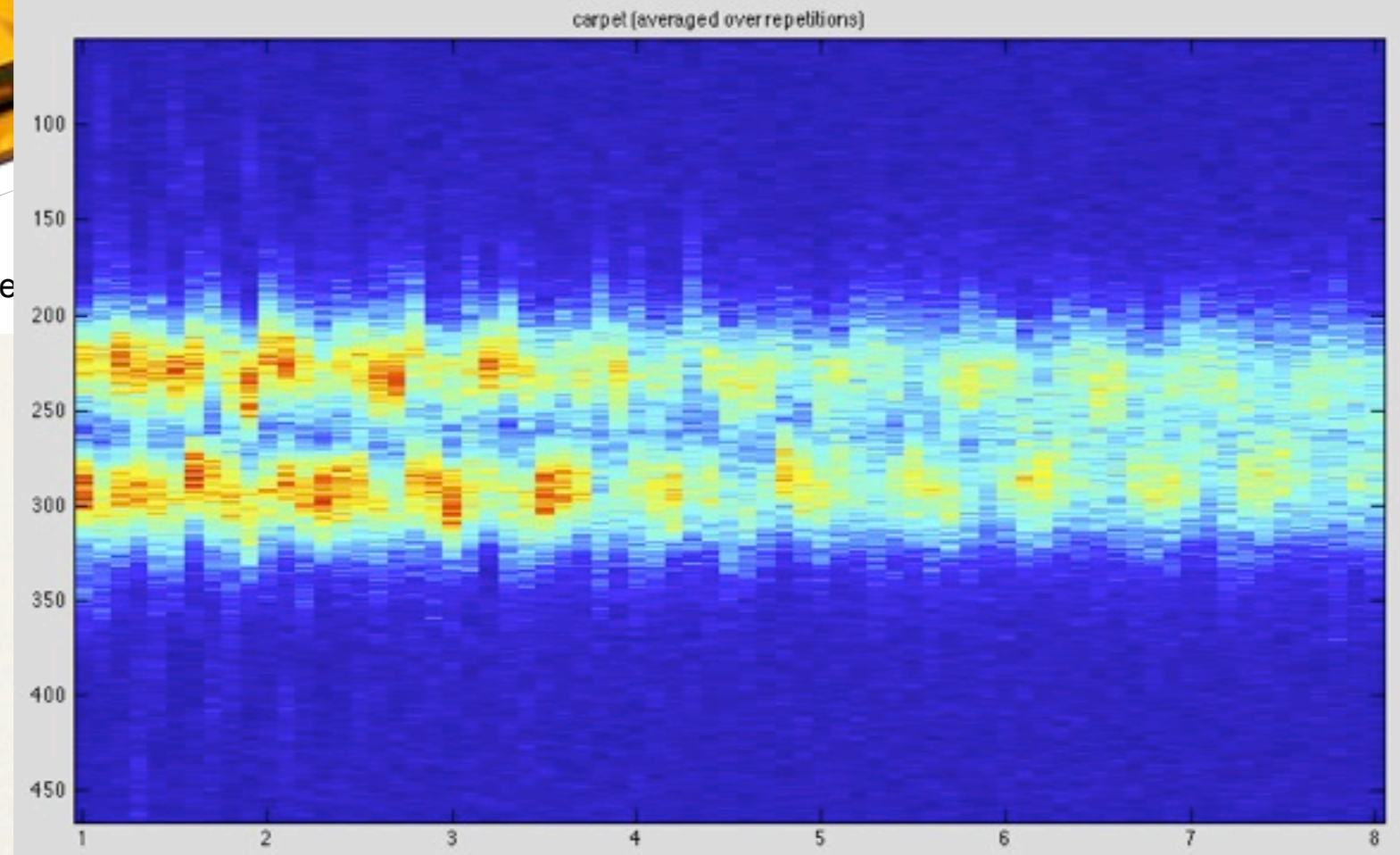
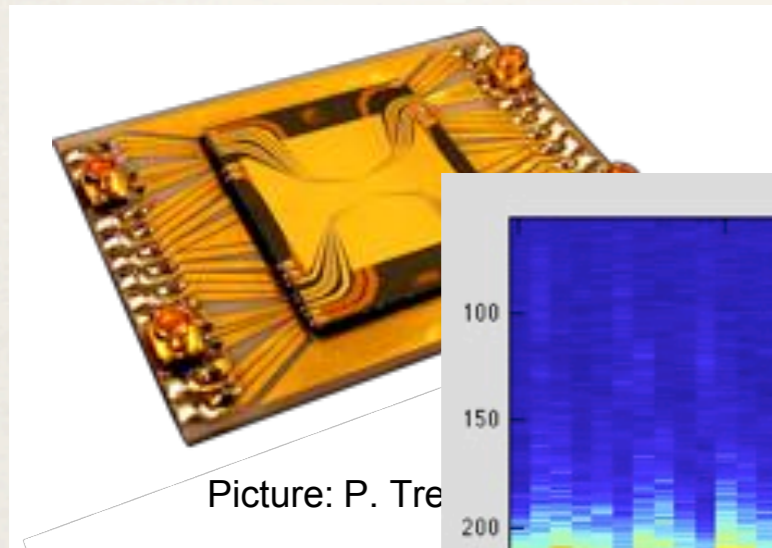
see also R. Büker et. al. Nat. Phys. 2011



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Atom chip experiments at QSL

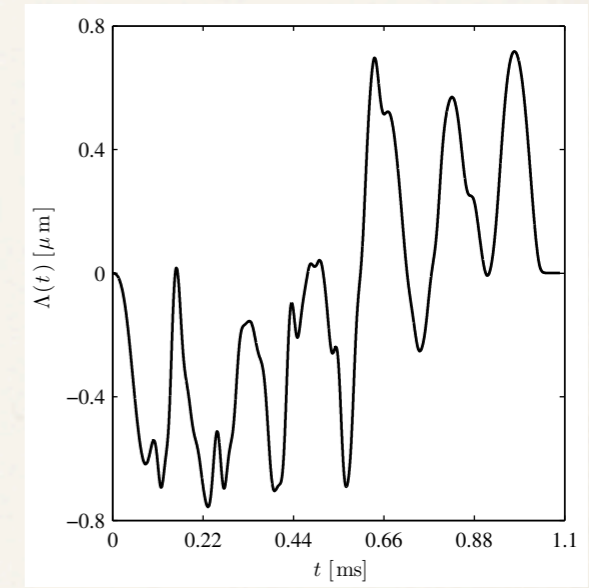
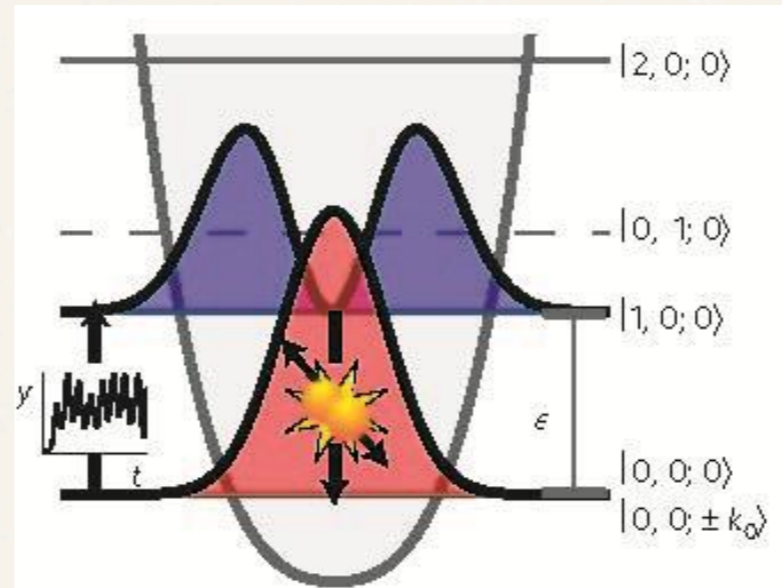
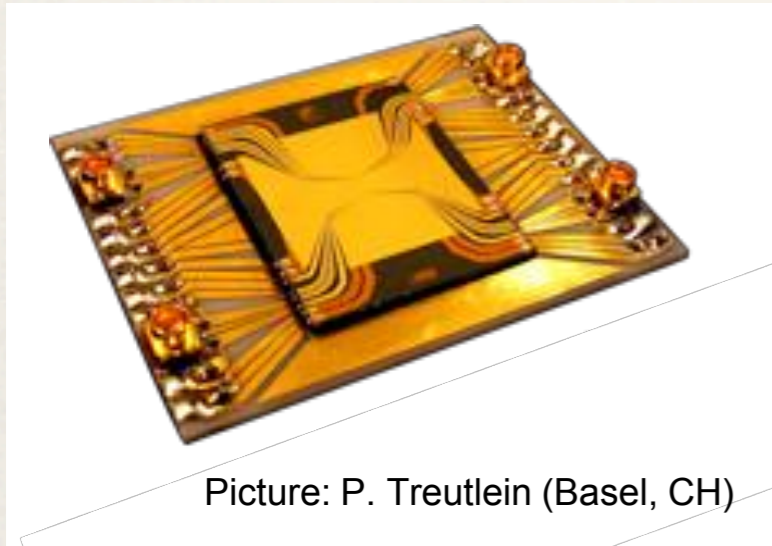
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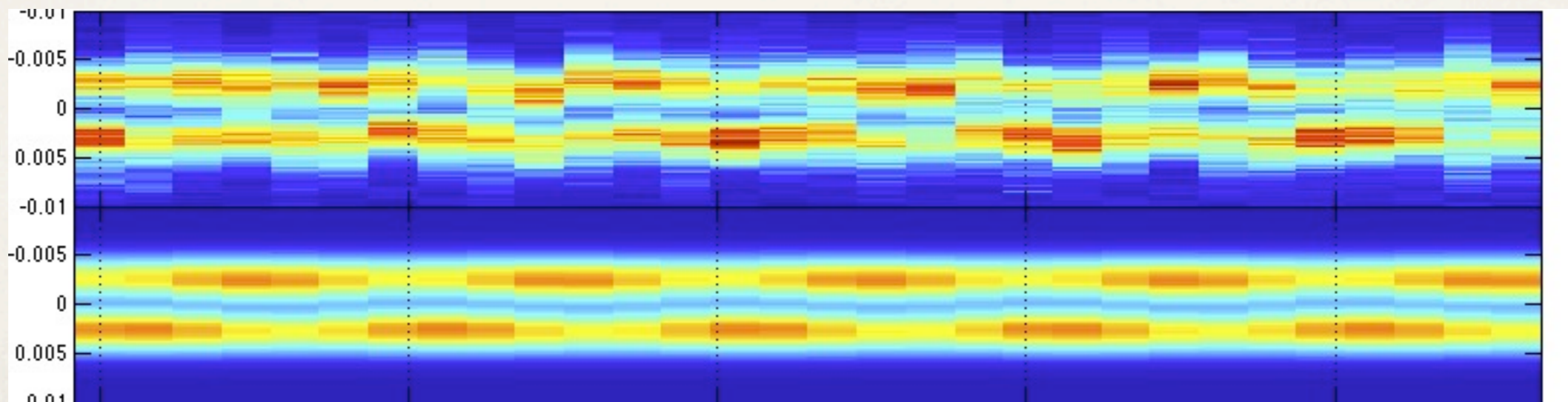
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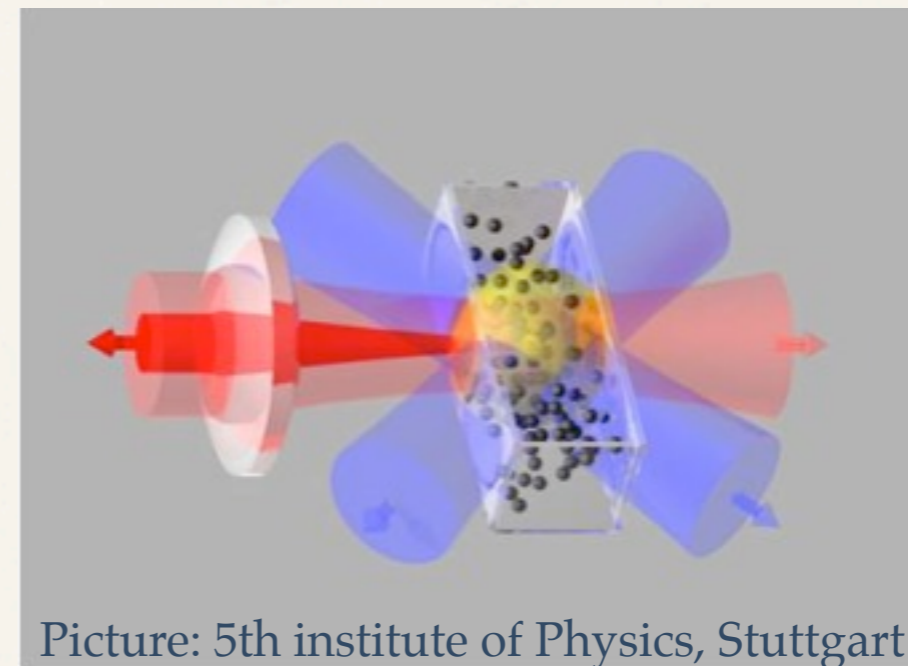
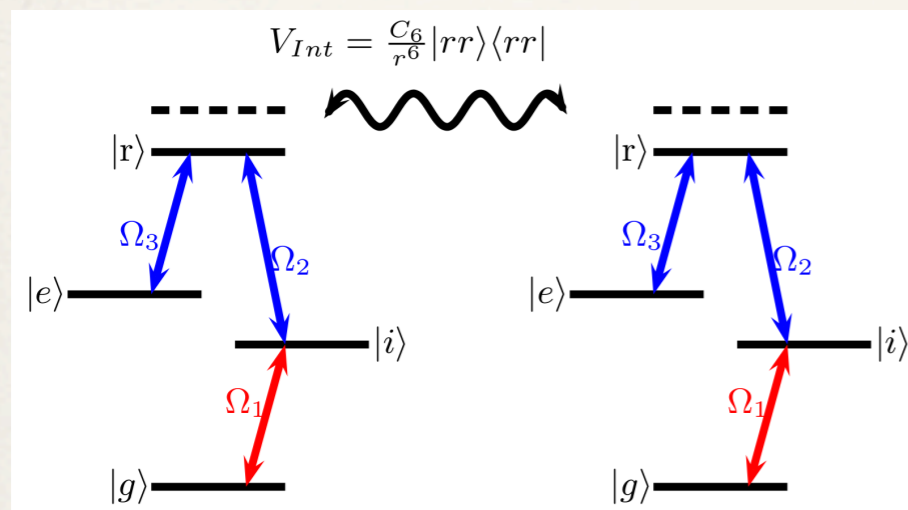


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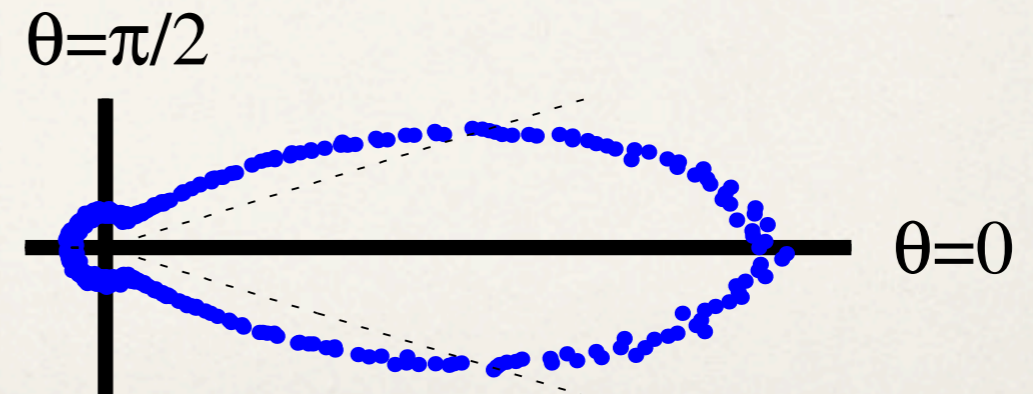
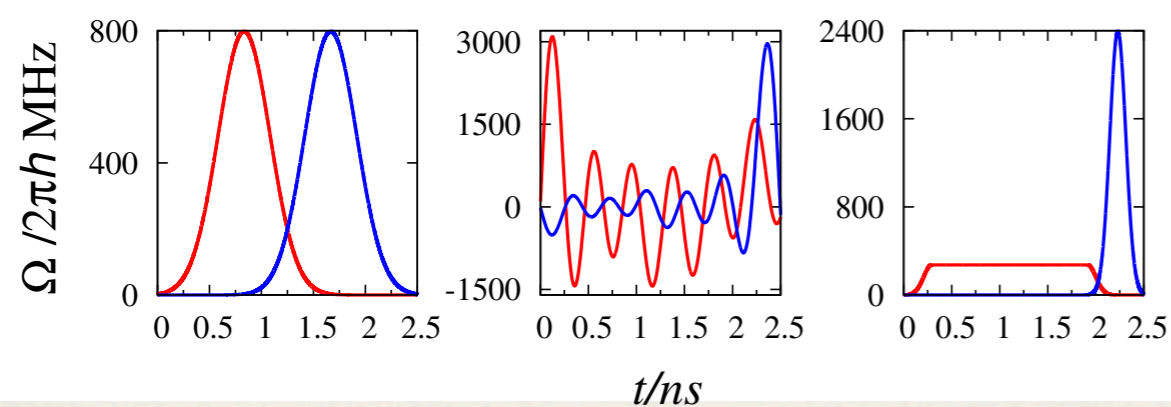
Single Photon Source at 30

20 min

Rydberg atoms



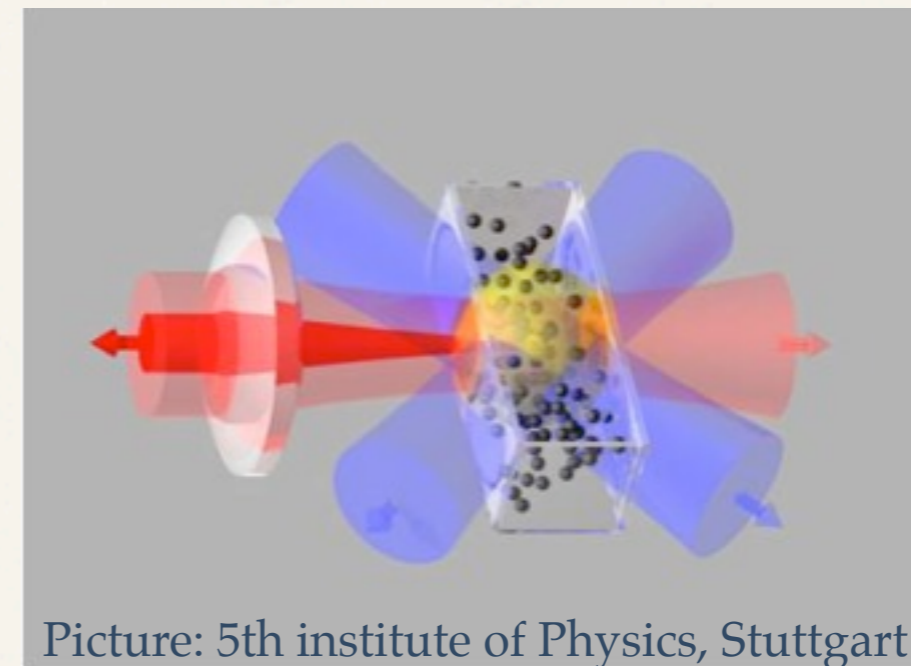
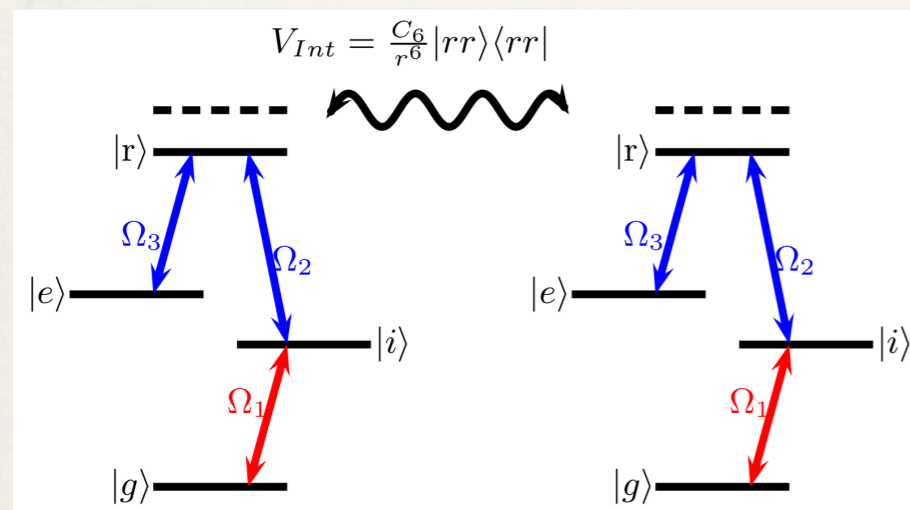
Picture: 5th institute of Physics, Stuttgart



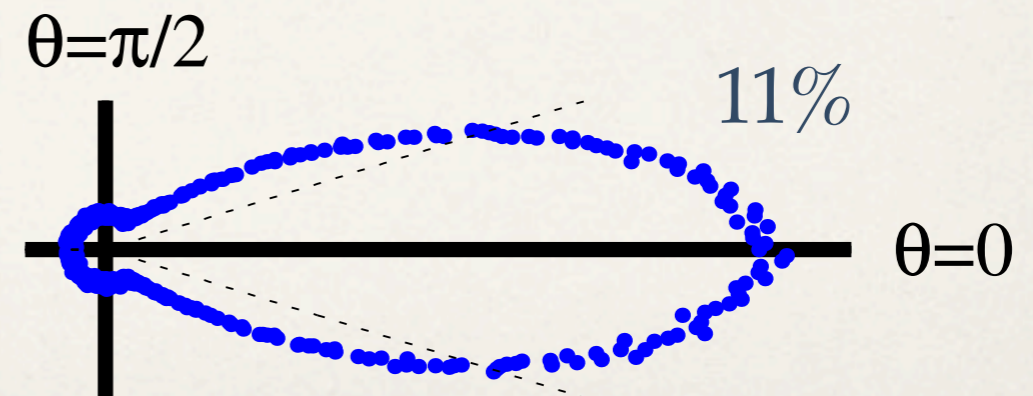
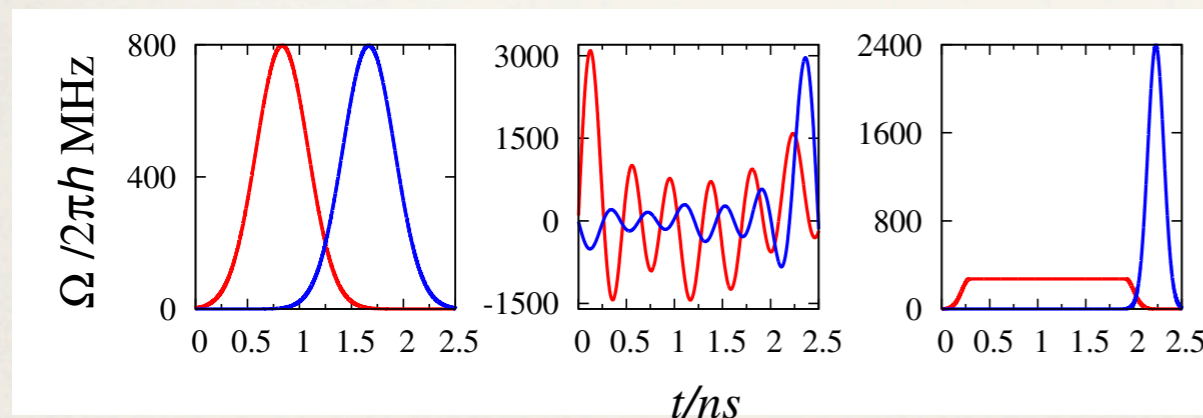
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Optimal control limits

Optimal control limits

- ❖ What are the physical limits of control of MBQS?

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Controllability, Reachability, Quantum Speed Limit, ...

Control complexity

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Control complexity

- ❖ What are the physical limits of control of MBQS?
Controllability, Reachability, Quantum Speed Limit, ...
- ❖ Are there any algorithmic/informational limits?
- ❖ How to characterize the complexity of the optimization task?

Assumptions

- ❖ Closed systems
- ❖ Many-body
- ❖ State to state transformation
- ❖ $H(t) = H_0 + \sum \lambda_j(t) H_j$
Drift Controls

Assumptions

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 $|\psi_0\rangle$

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Drift

Controls

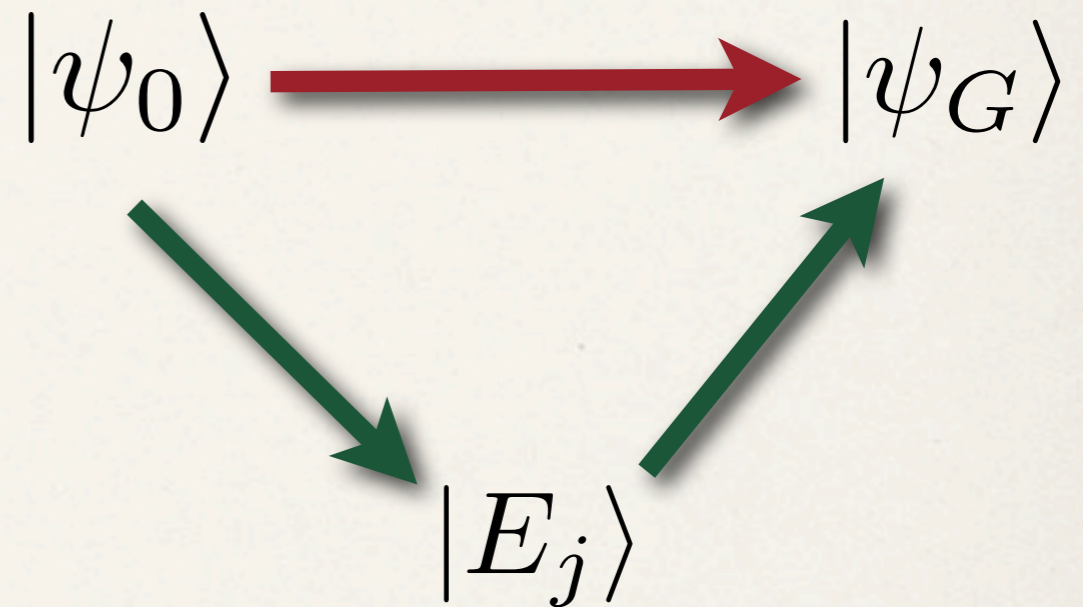
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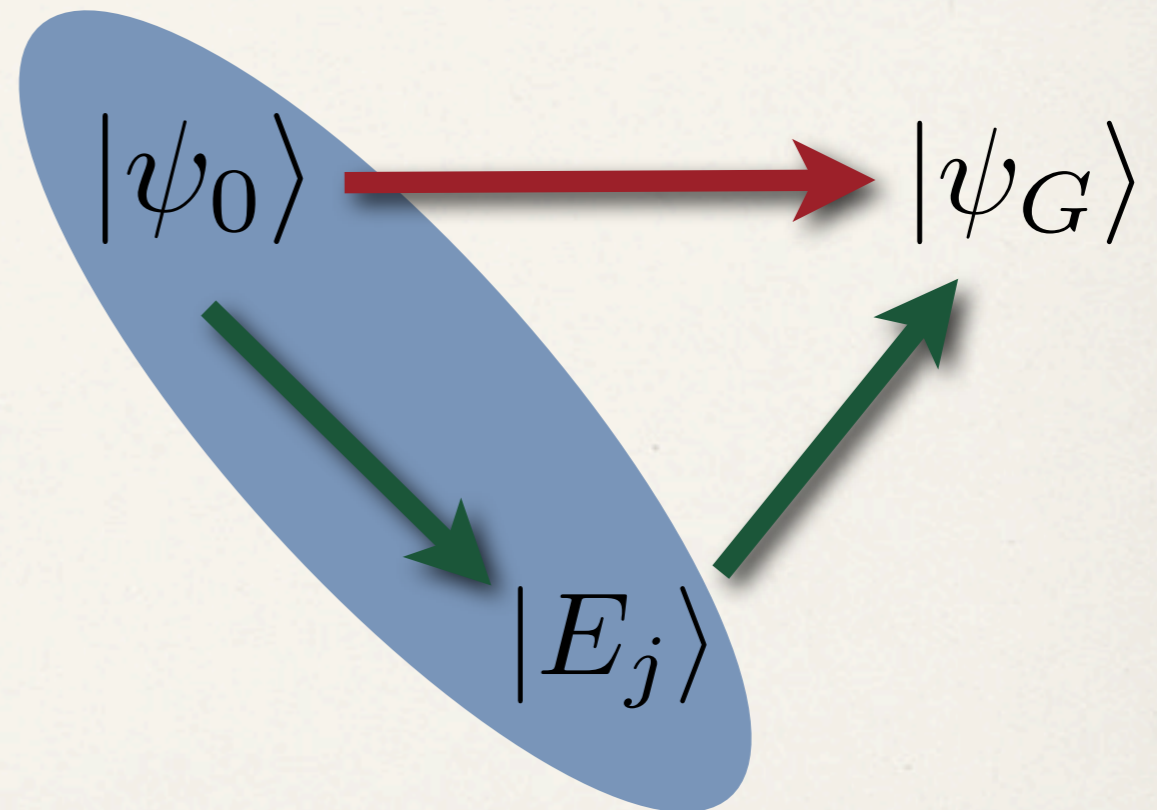
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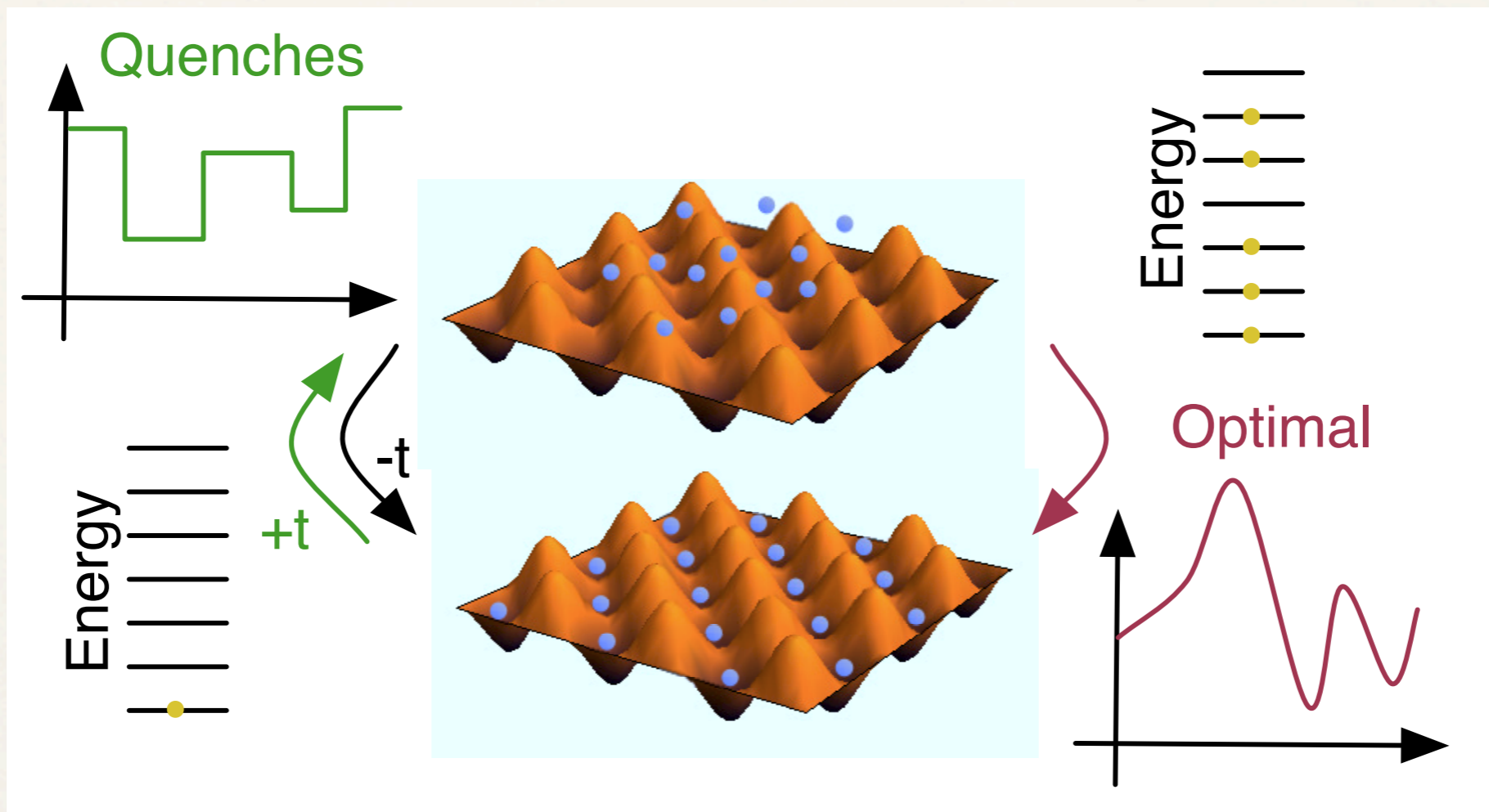


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Drift Controls



Reversibility



Is it possible? Is it difficult?

Diagonal Entropy

we are interested in quantifying the state complexity

$$S_d = - \sum \rho_{nn} \log \rho_{nn}$$

$$\rho = \sum \rho_{nm} |E_n(t)\rangle \langle E_m(t)|$$

$$H(t) = \sum E_n(t) |E_n(t)\rangle \langle E_n(t)|$$

- ✓ Introduces a preferred basis
- ✓ At equilibrium for diagonal states equal to VN entropy (positive, additive, 0 for T=0)
- ✓ Constant for stationary (diagonal) states
- ✓ Constant for adiabatic processes
- ✓ Only increases from stationary states in closed systems $S_d(T) \geq S_d(0)$
- ✓ Obeys fundamental Thermodynamical equation:

$$\Delta E = T \Delta S + \sum_j \left. \frac{\partial E}{\partial \lambda_j} \right|_S \Delta \lambda_j$$

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A. Polkovnikov, Annals of Physics (2011).

Diagonal entropy reduction

$S_d(0)$

⋮

$S_d(T)$

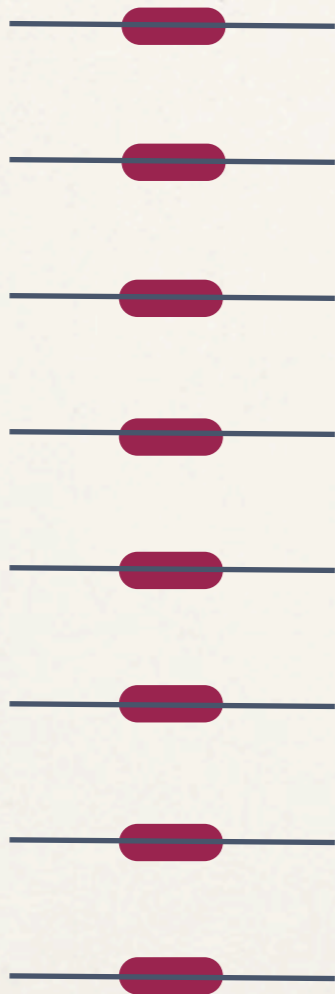
⋮

Control field?

Diagonal entropy reduction

$S_d(0)$

\vdots



$S_d(T)$

\vdots



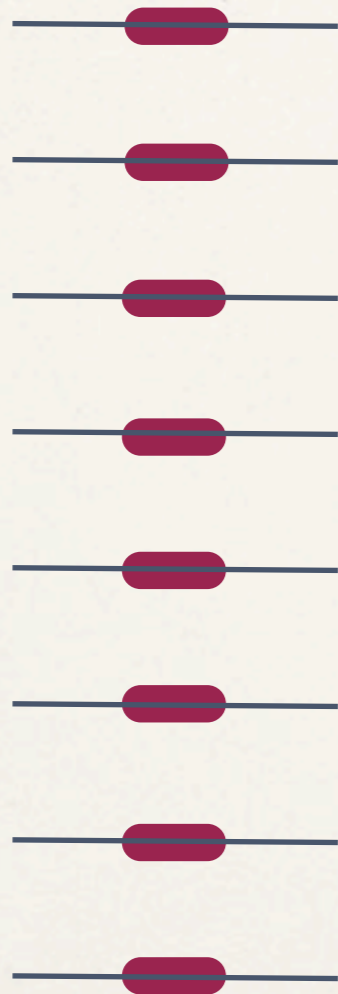
Control field?

$$|\psi(0)\rangle = \sum_{j=1}^N \frac{e^{i\phi_j}}{\sqrt{N}} |E_j(0)\rangle$$

Diagonal entropy reduction

$S_d(0)$

\vdots



$S_d(T)$

\vdots



Control field?

$$|\psi(0)\rangle = \sum_{j=1}^N \frac{e^{i\phi_j}}{\sqrt{N}} |E_j(0)\rangle$$

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Diagonal entropy reduction

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Reversed quantum dynamics

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Multiple random (time &
strength) quenches

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Initial ground state

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CRAB optimization

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$$H = - \sum_{i,j} J_{ij} \sigma_i^x \sigma_j^x - \Gamma(t) \sum_i \sigma_i^z$$

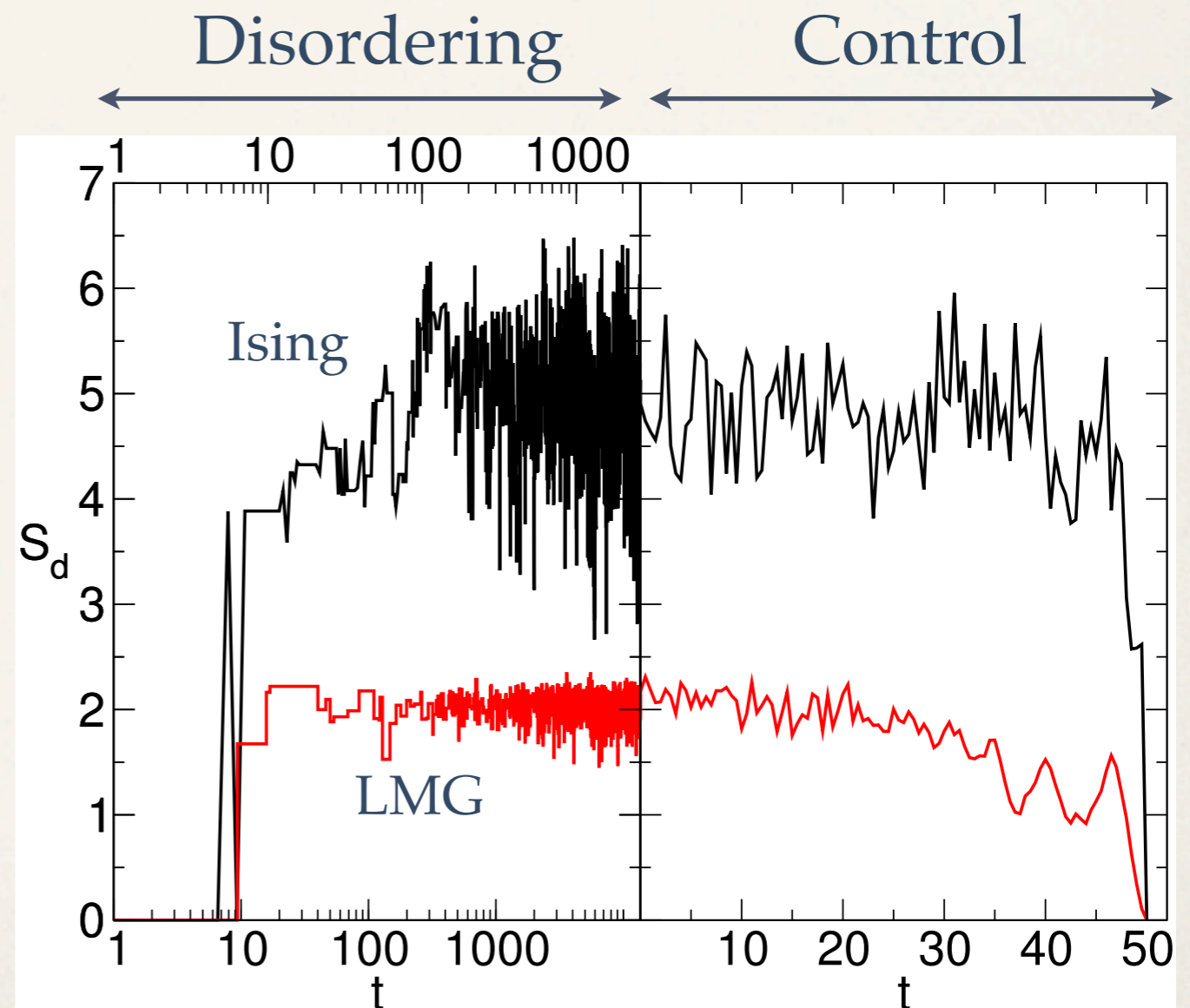
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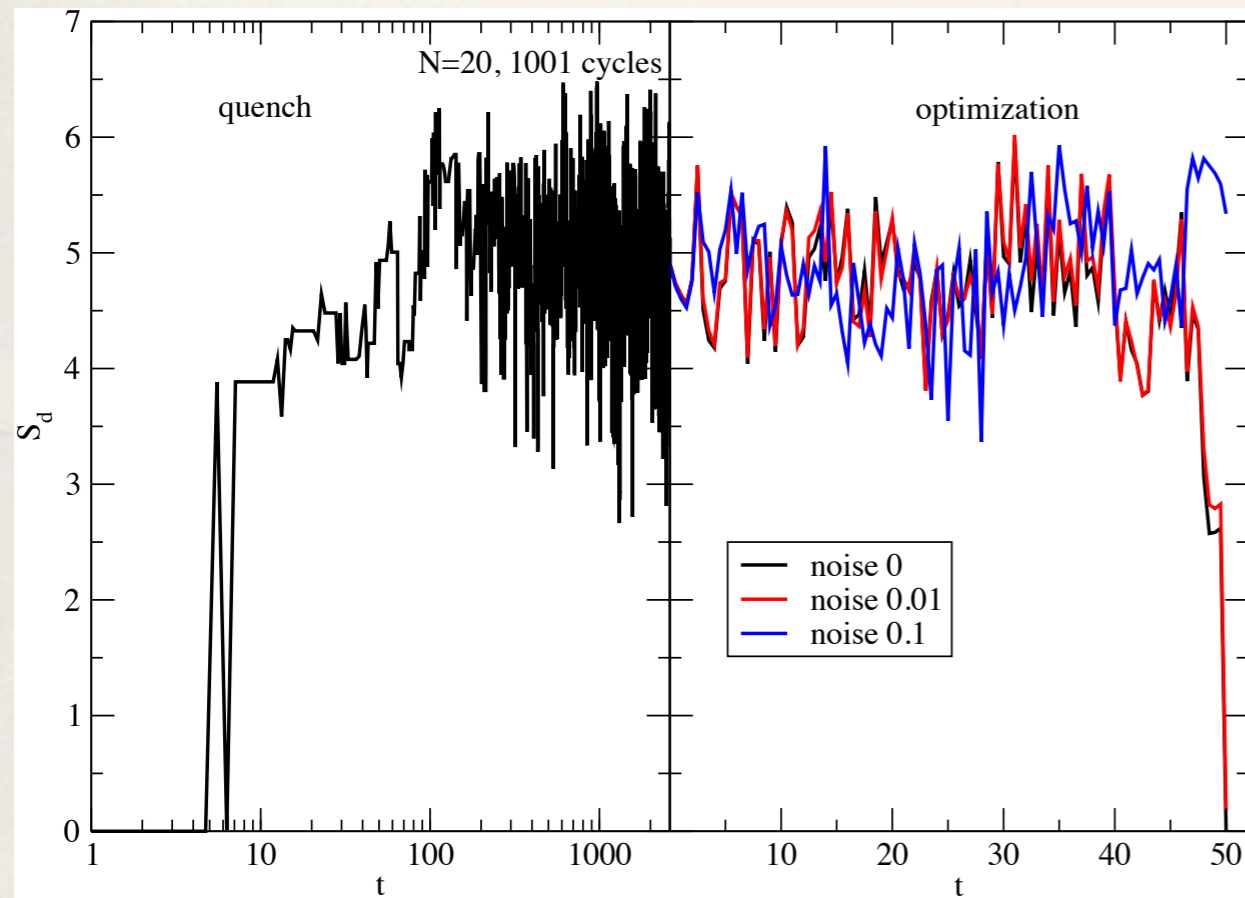


Robustness

Is all that robust against noise?

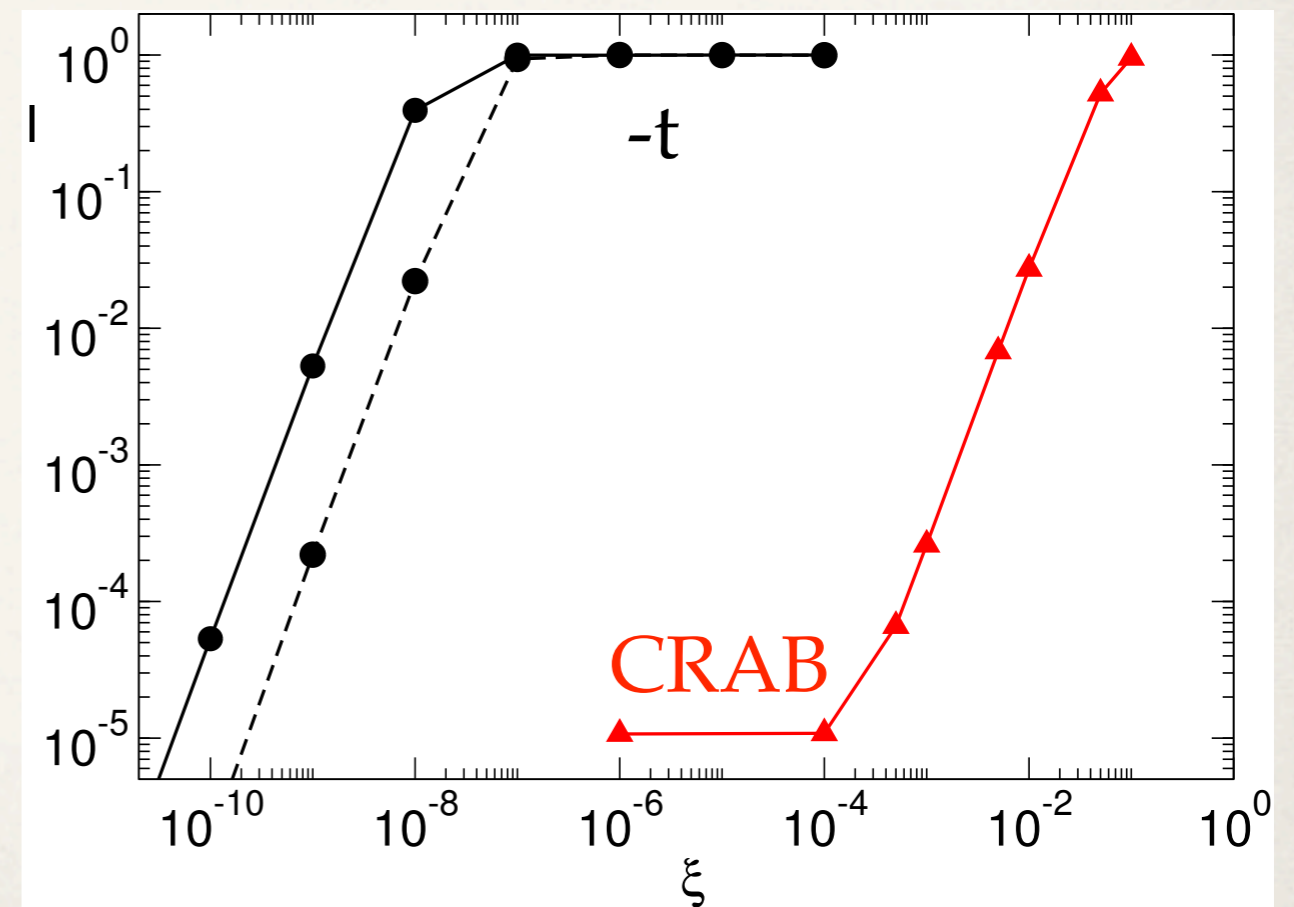
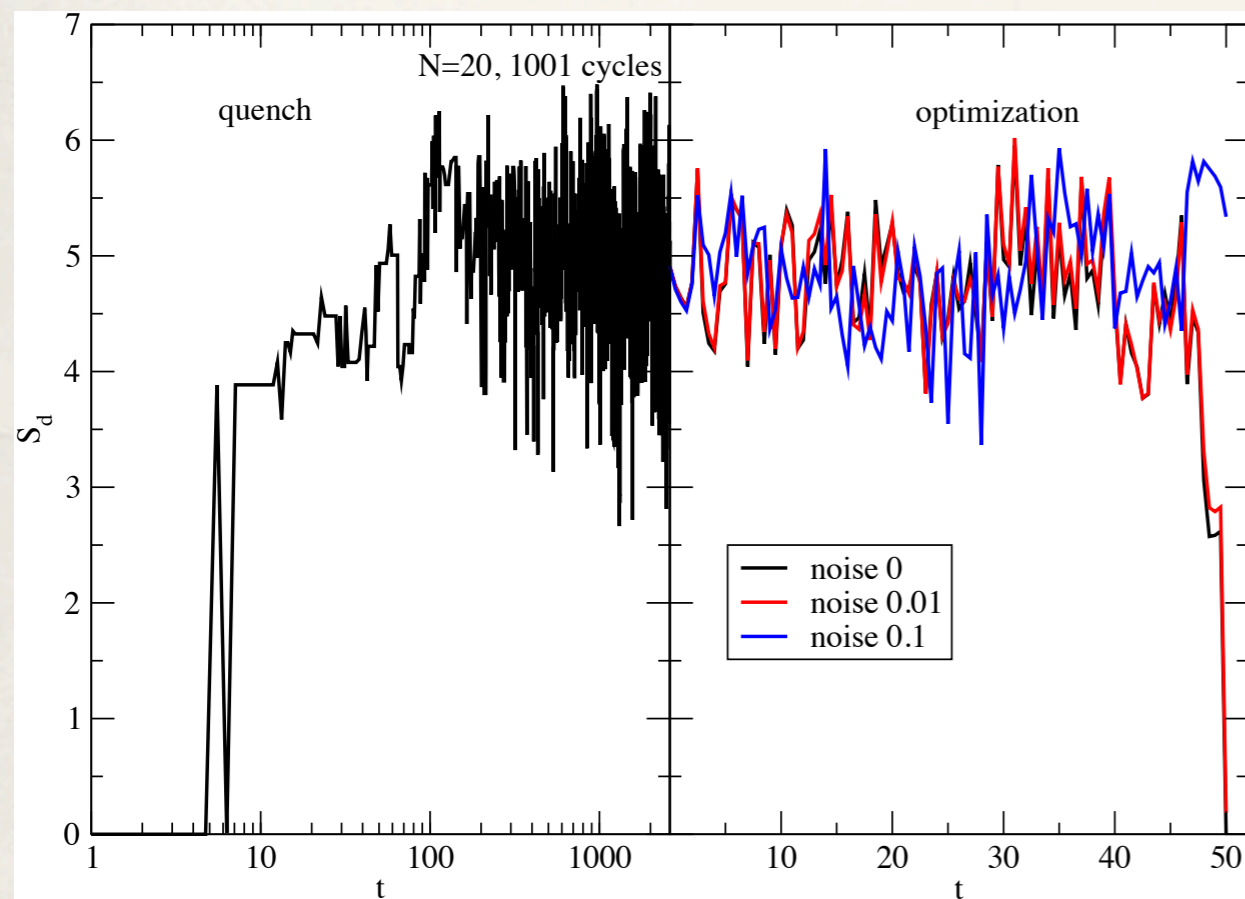
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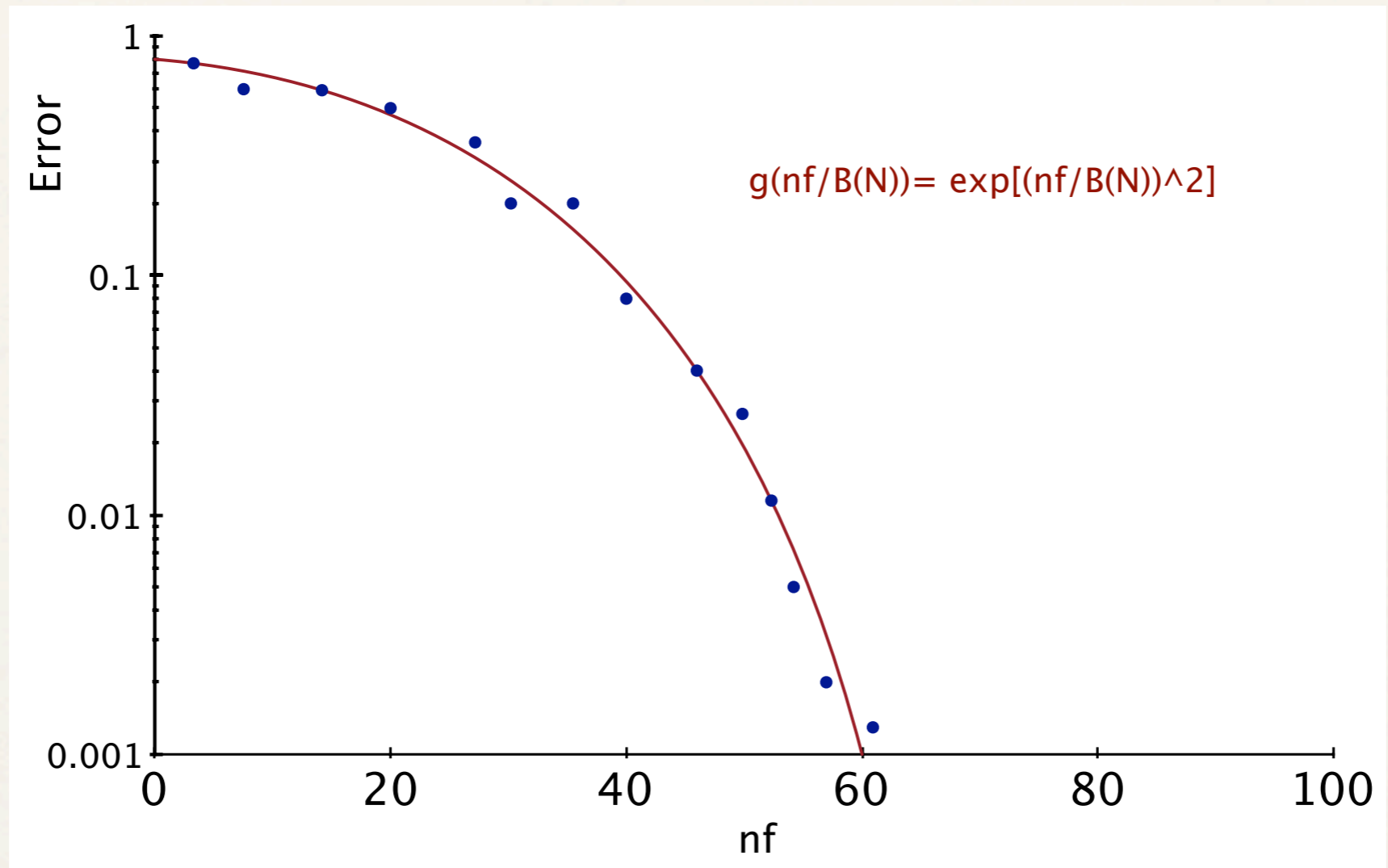


Robustness

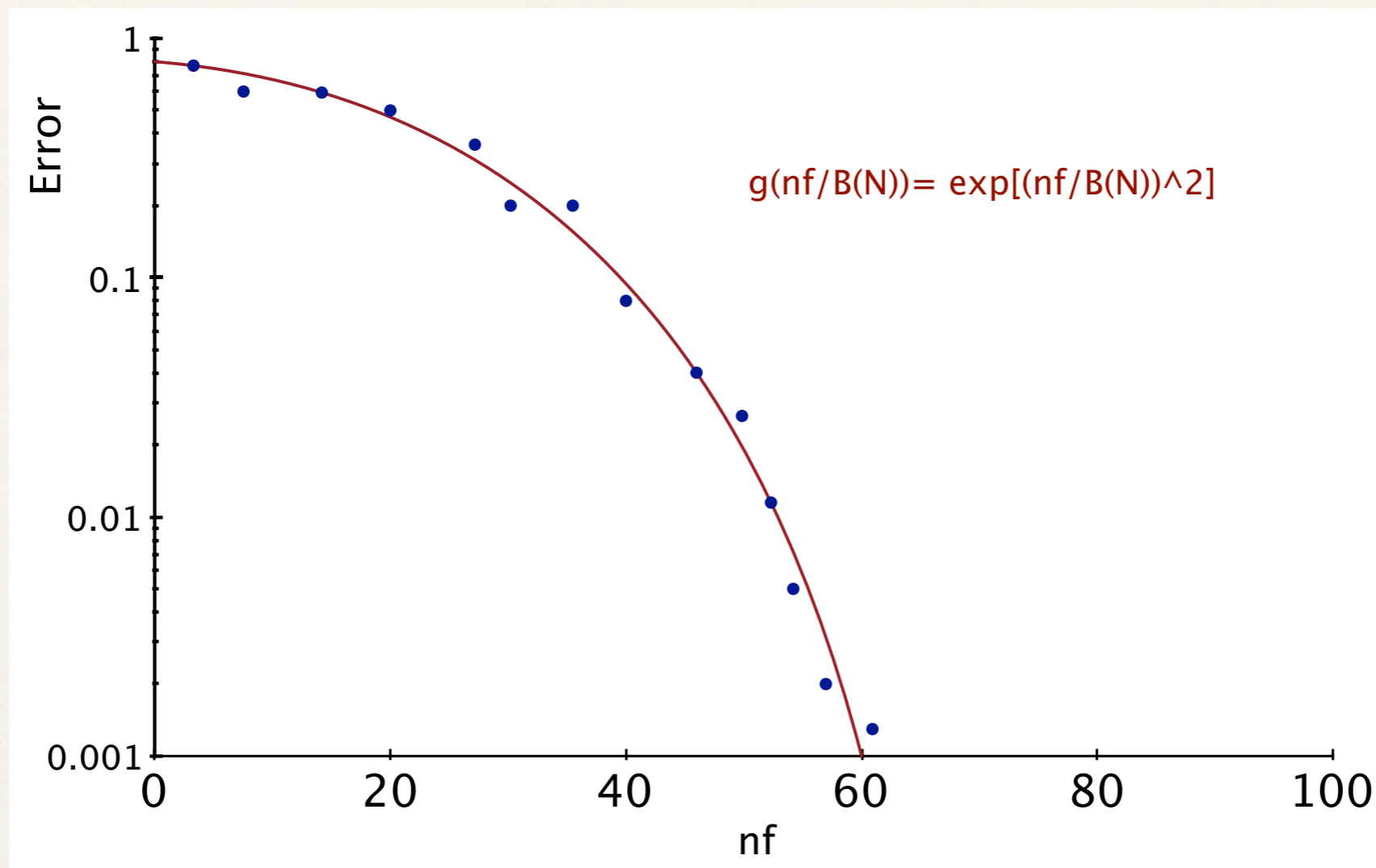
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Complexity



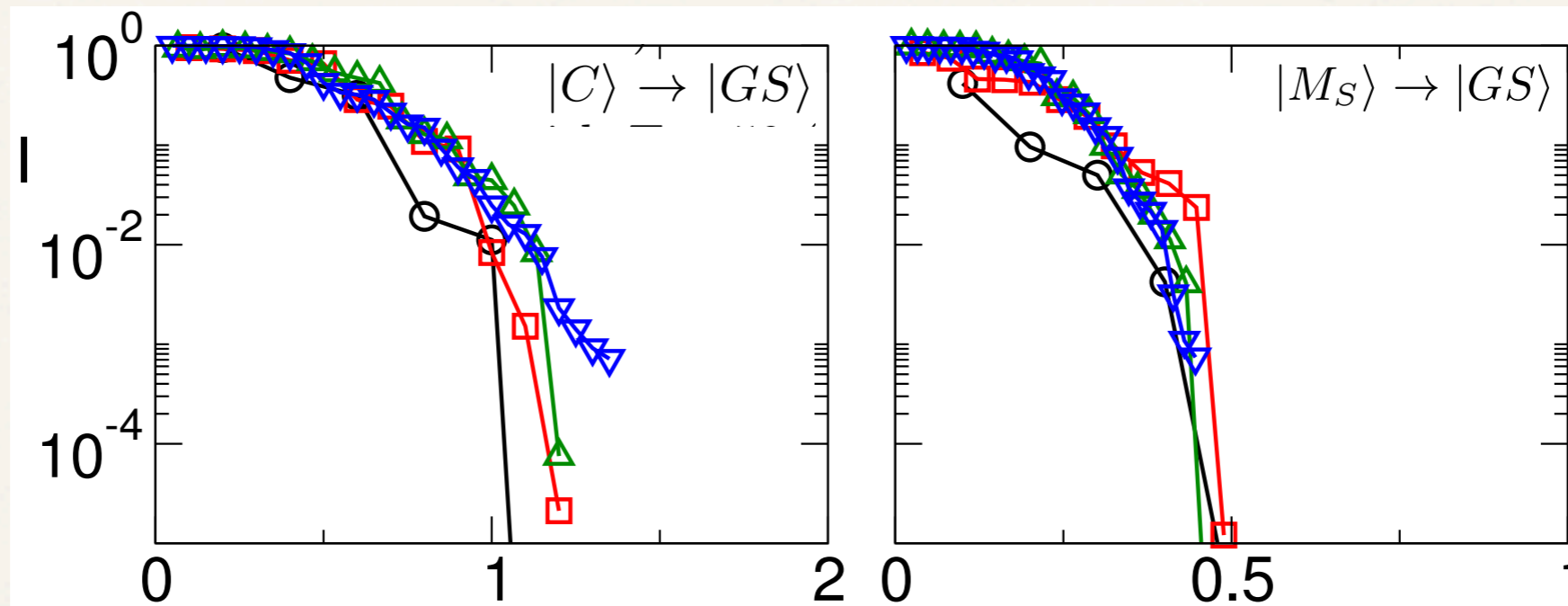
Complexity



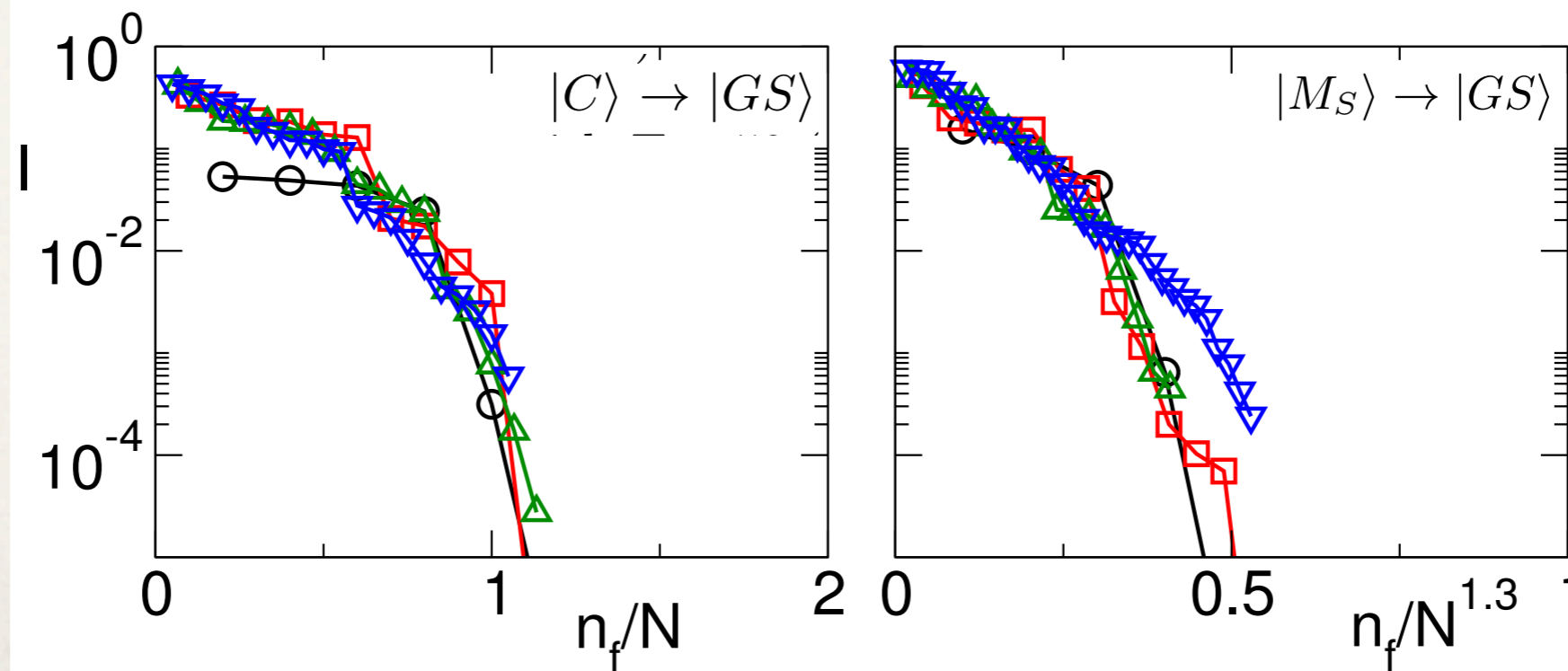
Scaling of the number of parameters with the system size $B(N)$

Reversibility and Information

Ising



LMG



$N=10, \dots, 40$

Conjecture

Conjecture

The complexity of the control task (control bandwidth) scales as the dimension of the accessible Hilbert space

Conjecture

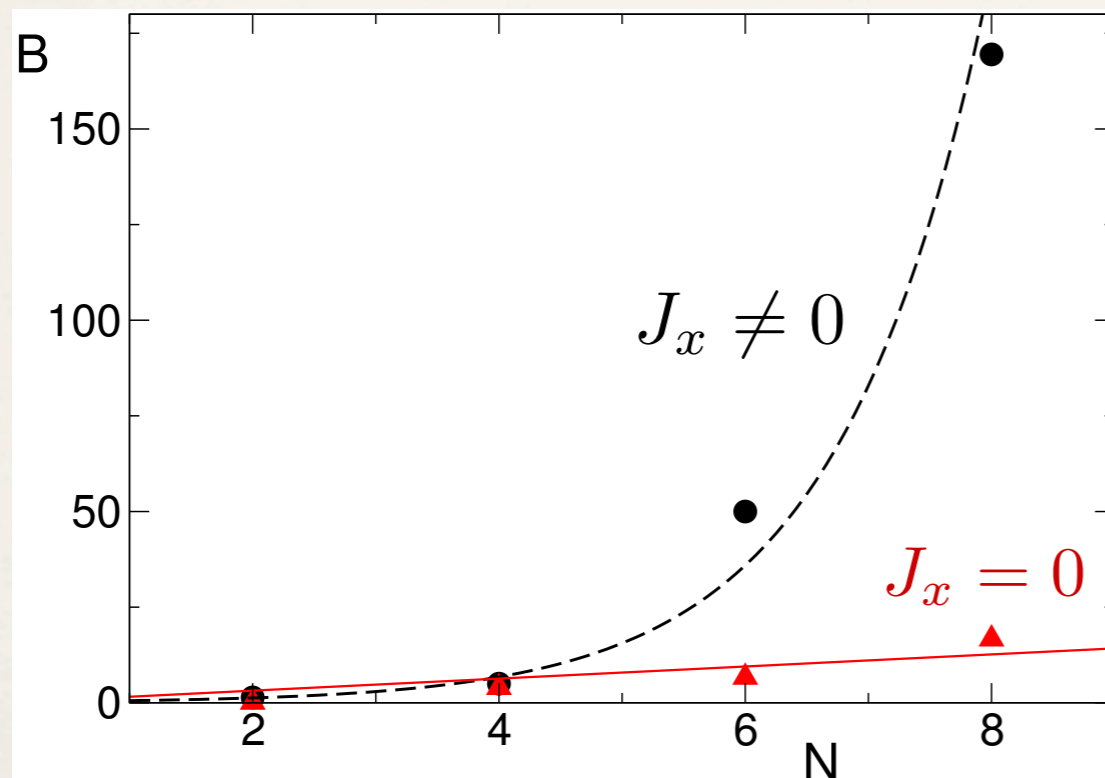
The complexity of the control task (control bandwidth) scales as the dimension of the accessible Hilbert space

$$H = - \sum_{i,j} J_{ij} \sigma_i^x \sigma_j^x - \Gamma(t) \sum_i^N \sigma_i^z - J_x \sum_i^N \sigma_i^x$$

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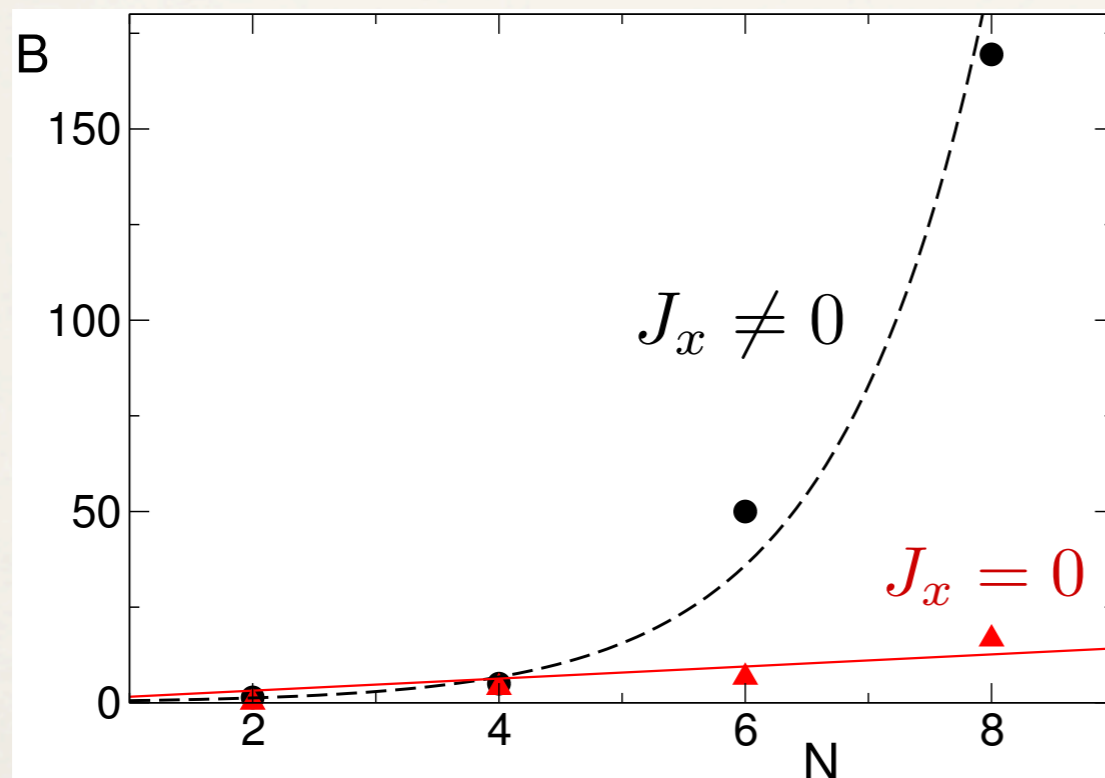
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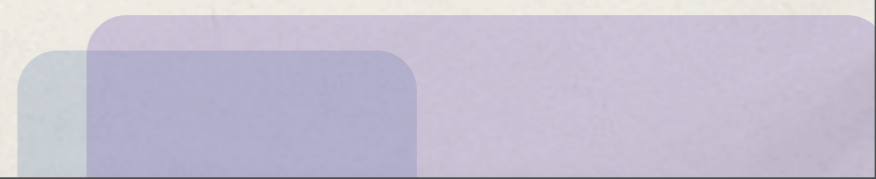
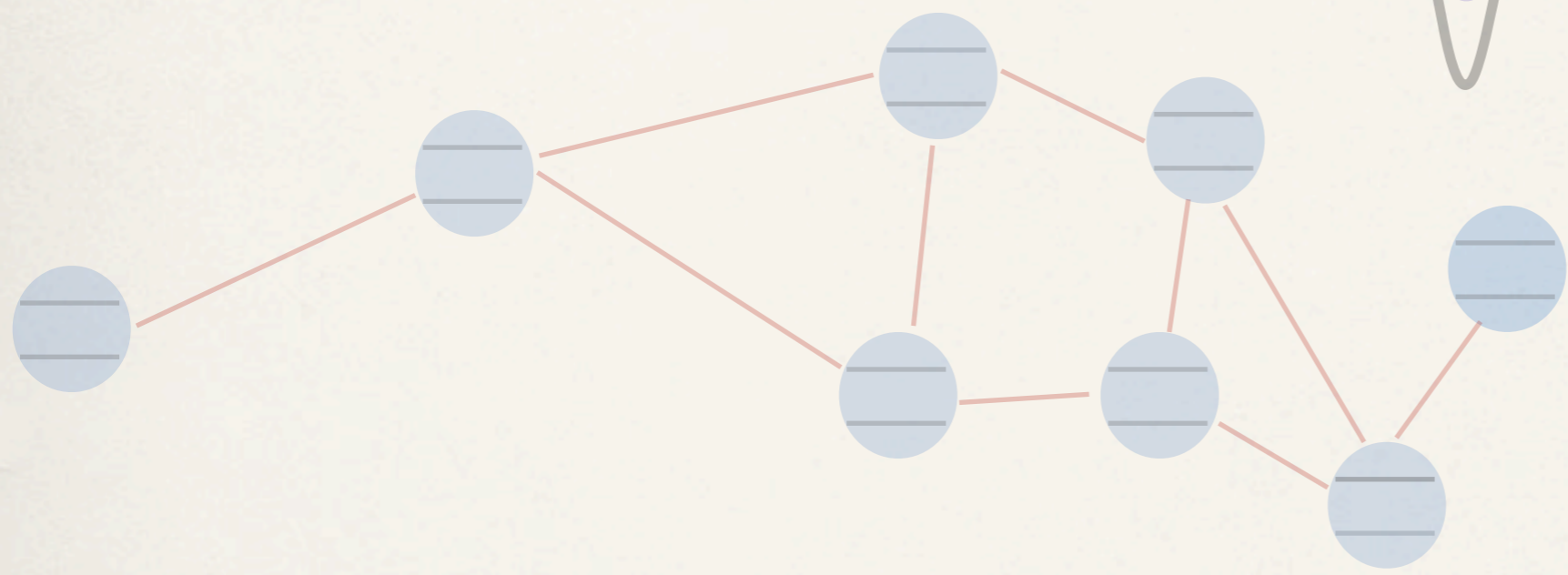
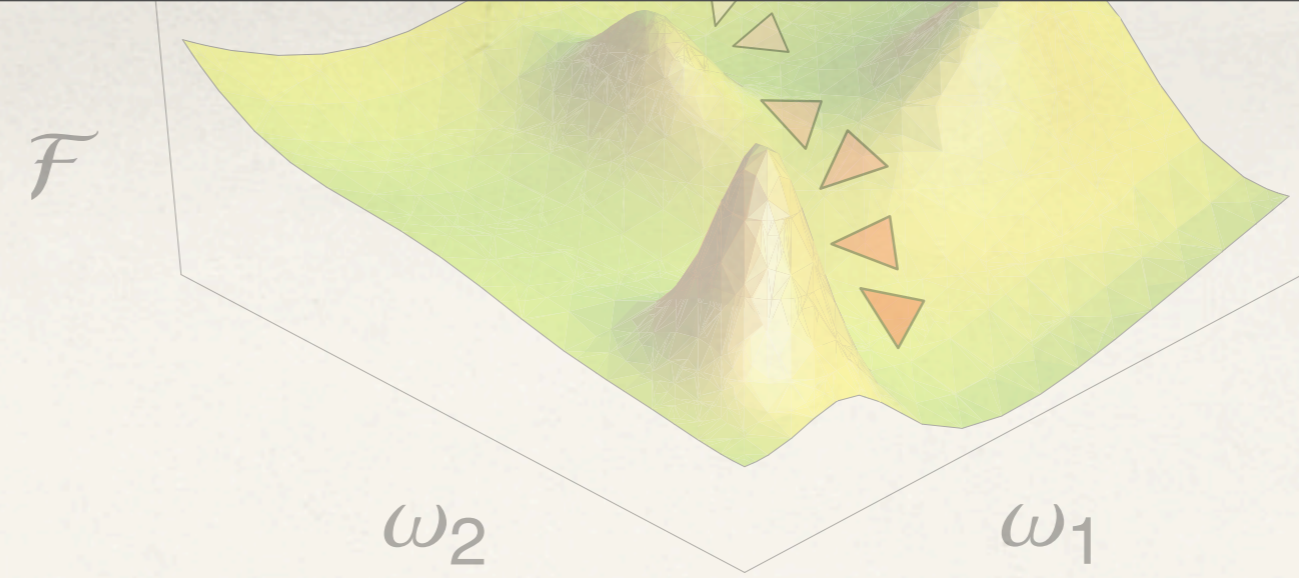
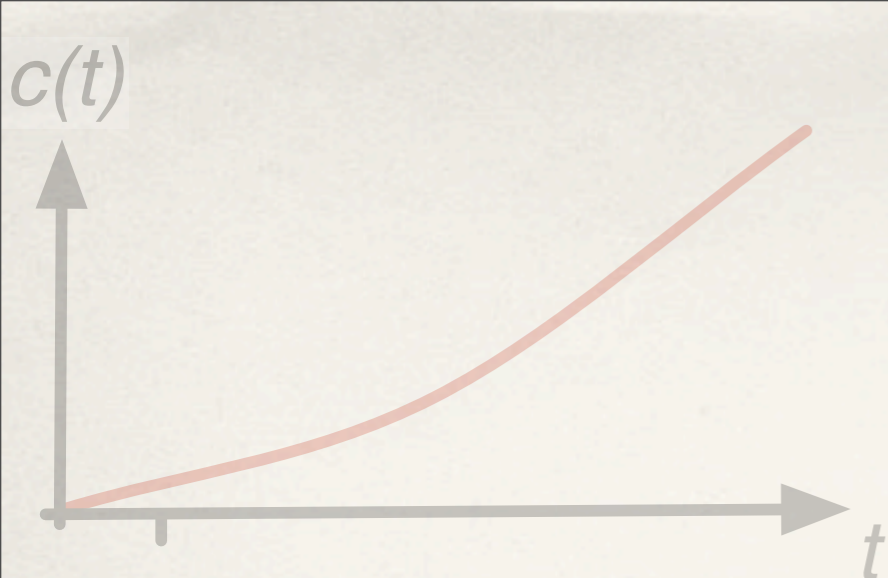
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$$B(N) \propto D_m(N)$$

Conclusions

- * CRAB optimization can be applied successfully to MBQS dynamics opening new perspectives.
- * Using optimal control it is possible investigate qualitatively new phenomena
- * Optimal trajectories are robust with respect to noise and perturbations.
- * Complexity of control task can be characterized by the degrees of freedom of the optimal driving field.
- * Non-integrable MBQS are exponentially complex to be optimized



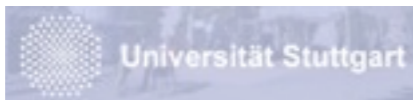
$c(t)$

Thank you for your attention!



In collaboration with:

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Thomas Pichler
Susana Huelga
Martin Plenio
Filippo Caruso



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Thorsten Schumm
Sandrine van Frank
Wolfgang Rohringer



Funds:

SFB / TRR21 Co.Co.Mat.



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Numerics:

BW-Grid

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