

# Tensor networks: simulating quantum many-body systems and beyond

Simone Notarnicola, University of Padova, INFN, Italy



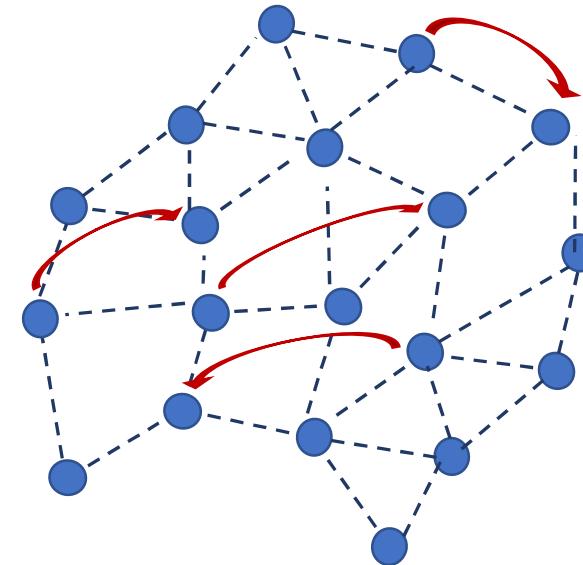
# Introduction: quantum many-body systems

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## Quantum many-body systems

- Quench dynamics
- Ground state properties
- ...

Correlations → Entanglement



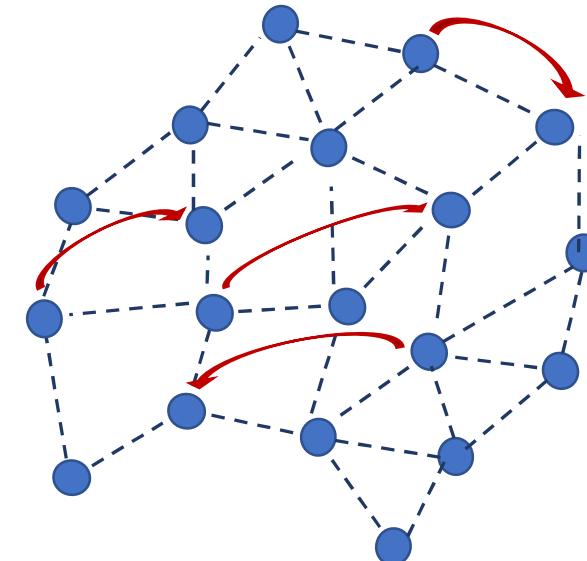
# Introduction: quantum many-body systems

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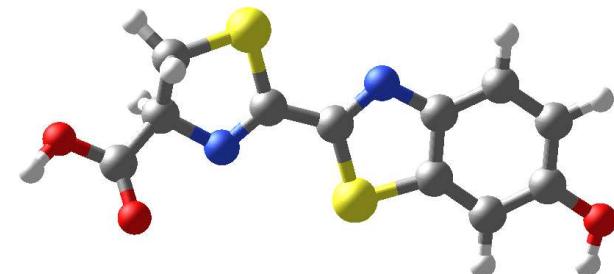
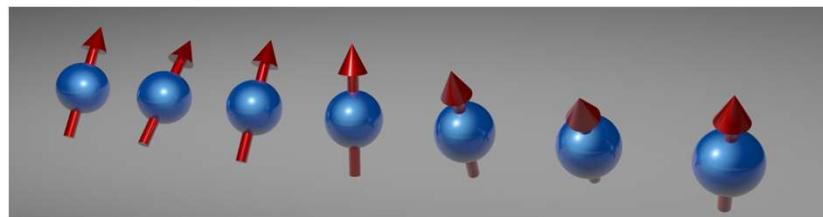
## Quantum many-body systems

- Quench dynamics
- Ground state properties
- ...

Correlations → Entanglement



- Condensed matter
- Quantum chemistry
- ...



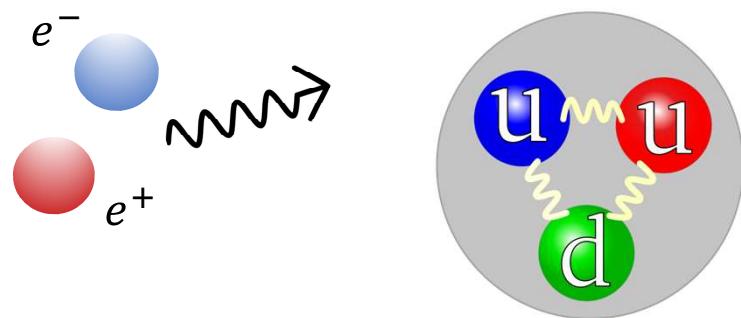
Phys. Rev. Lett. 119, 080501 (2017)

Credits: Maple Quantum Chemistry

# Gauge theories

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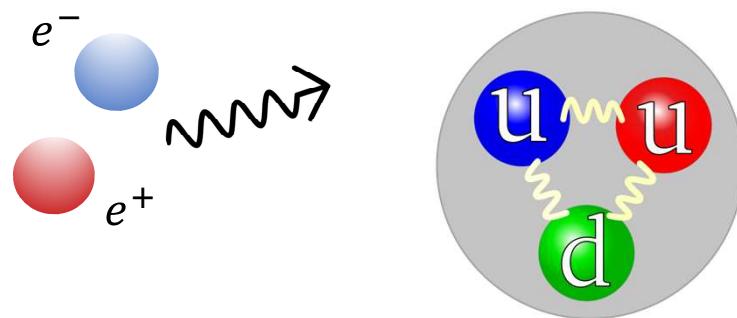
Fundamental interactions of matter



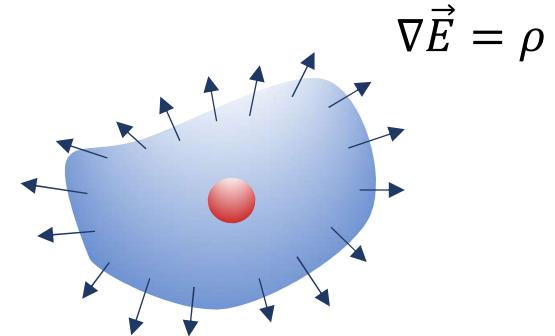
# Gauge theories

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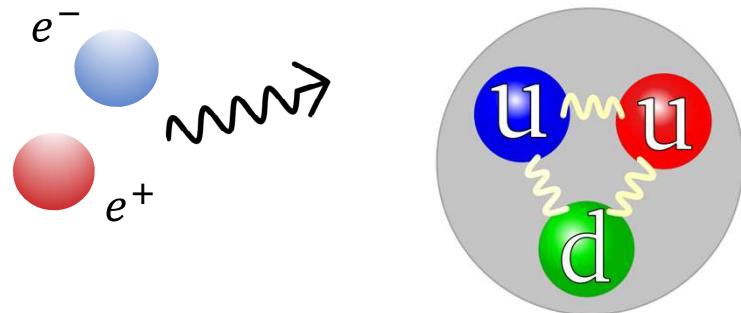
Interactions arise by imposing  
local conservation Gauss' laws



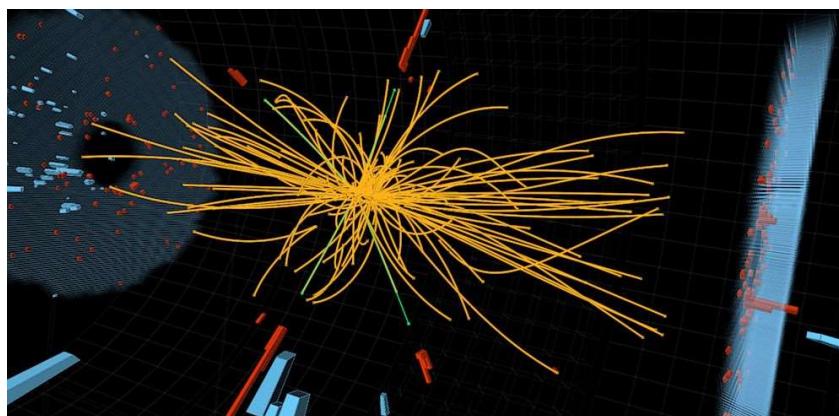
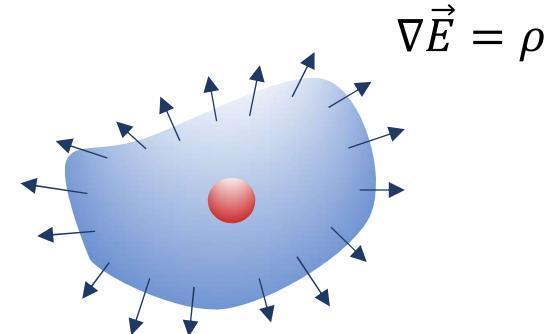
# Gauge theories

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Fundamental interactions of matter



Interactions arise by imposing local conservation Gauss' laws



Simulating gauge theories:

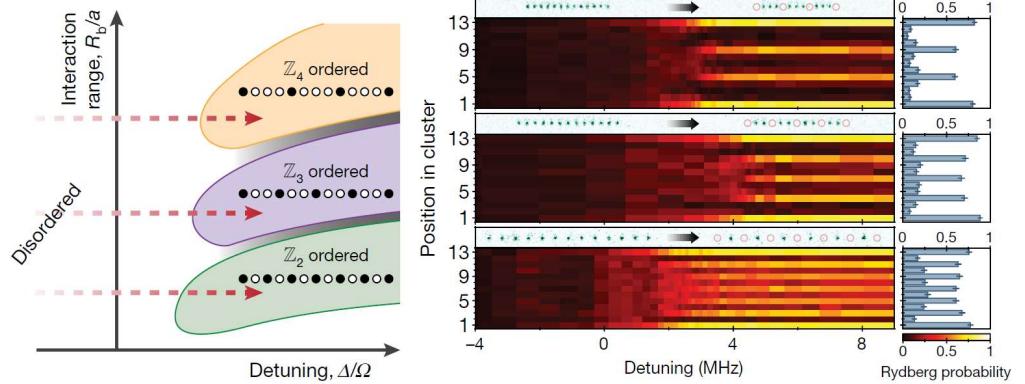
- Huge Hilbert space dimension
- Sign problem

# Introduction: quantum computations

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Recent technological achievement:

- Rydberg atoms chains

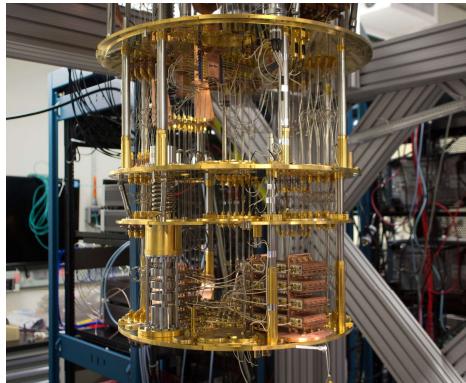
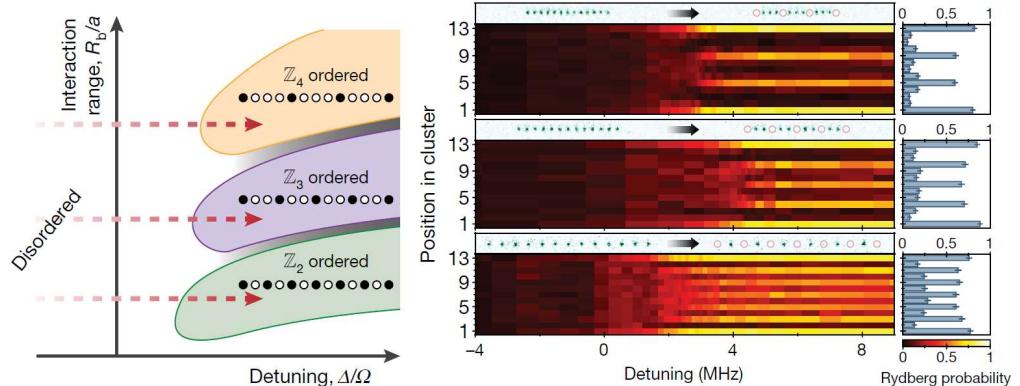


Nature 551, 579 (2017)

# Introduction: quantum computations

Recent technological achievement:

- Rydberg atoms chains
- Trapped ions
- Superconducting-qubits quantum computers



IBM quantum computer



Google quantum computer

Needed:

- Benchmark
- Validation

# Quantum simulation of Lattice Gauge Theories

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Simulating a quantum theory through a controllable quantum system

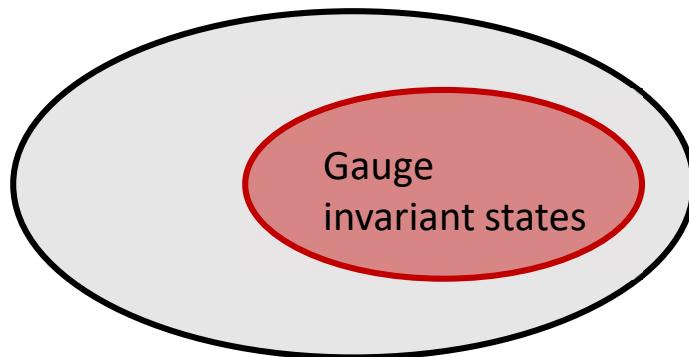
# Quantum simulation of Lattice Gauge Theories

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Simulating a quantum theory through a controllable quantum system

- Mapping between the Hilbert spaces
- Mapping between the Hamiltonians

Quantum simulator  
Hilbert space

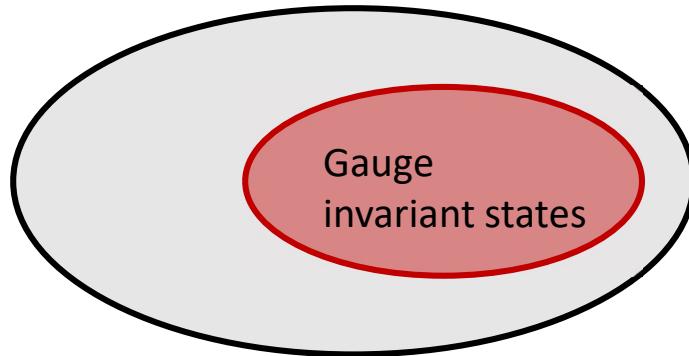


# Quantum simulation of Lattice Gauge Theories

Simulating a quantum theory through a controllable quantum system

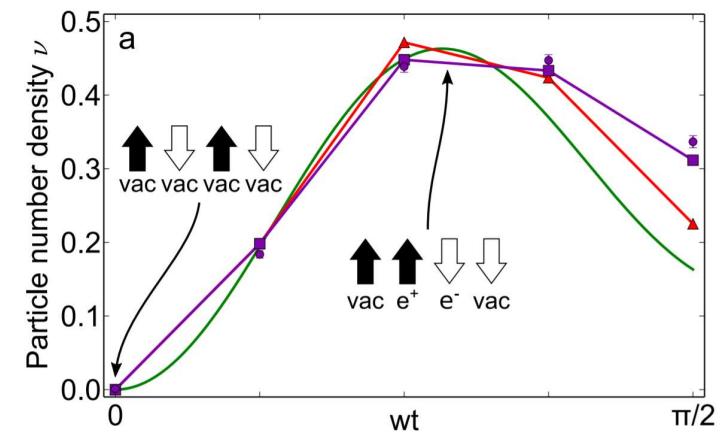
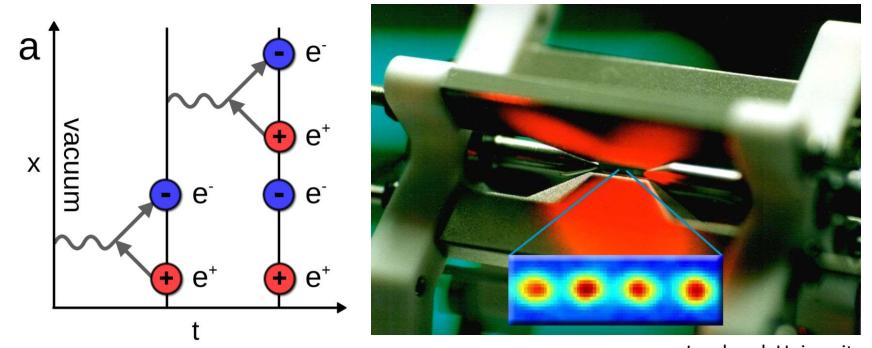
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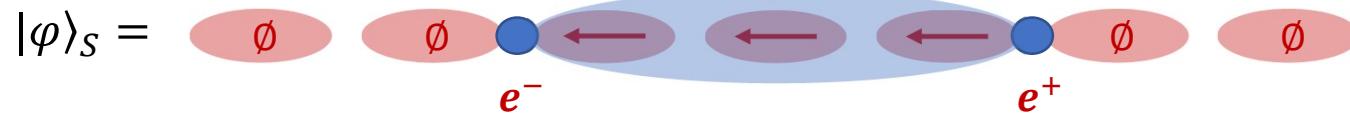
1D Schwinger model:  
Fermions coupled to an electric gauge field

Trapped ions:  
two relevant internal states implement a qubit

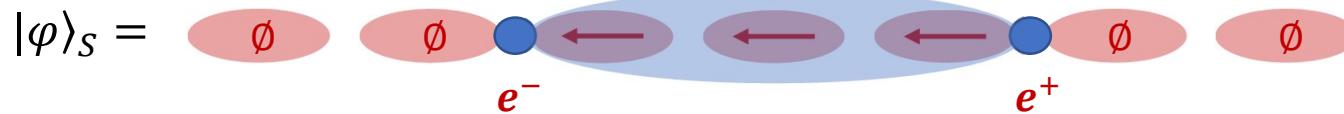


# Quantum simulation of Lattice Gauge Theories

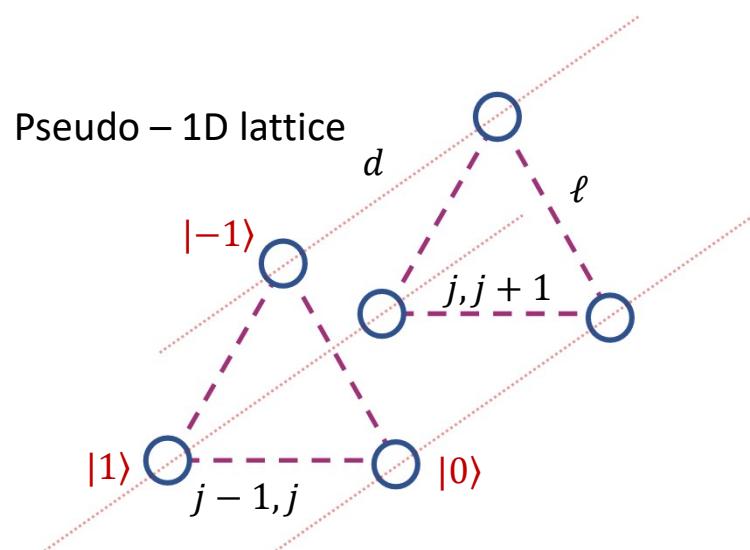
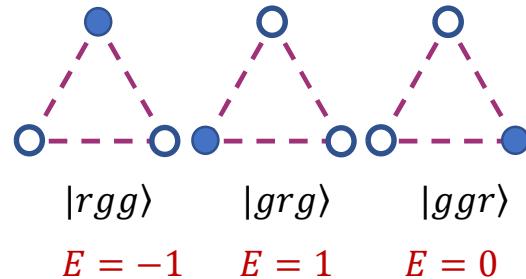
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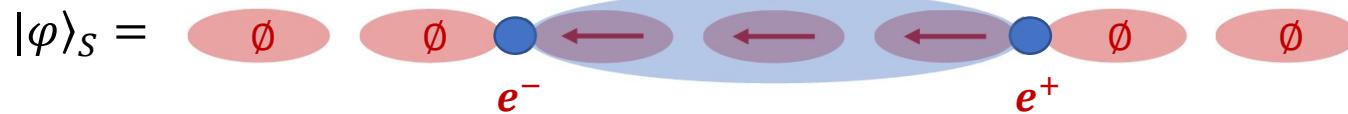
# Quantum simulation of Lattice Gauge Theories



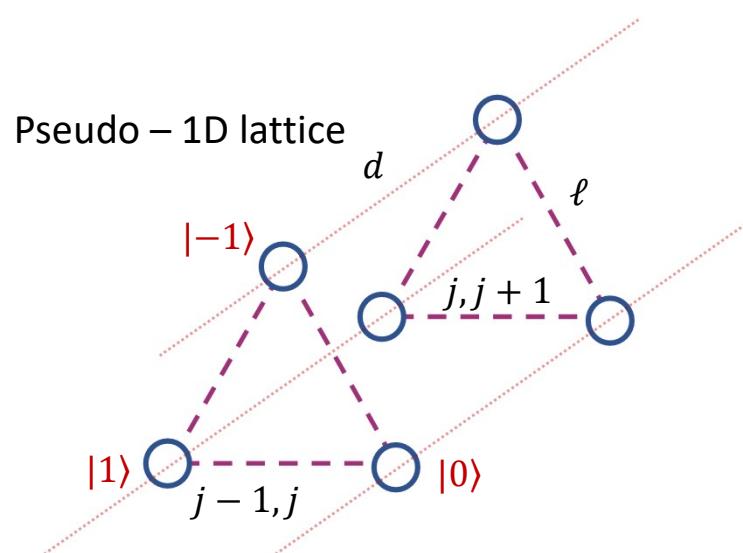
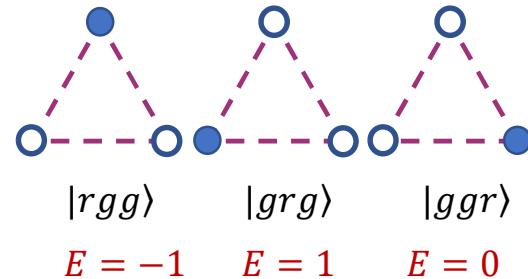
Three atoms represent a link



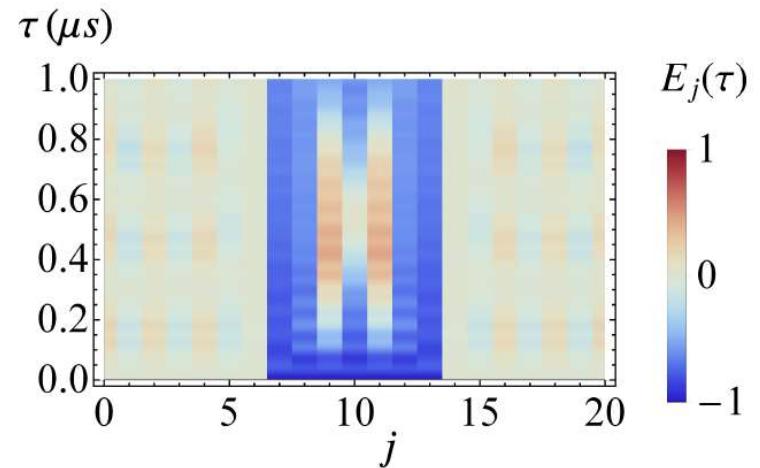
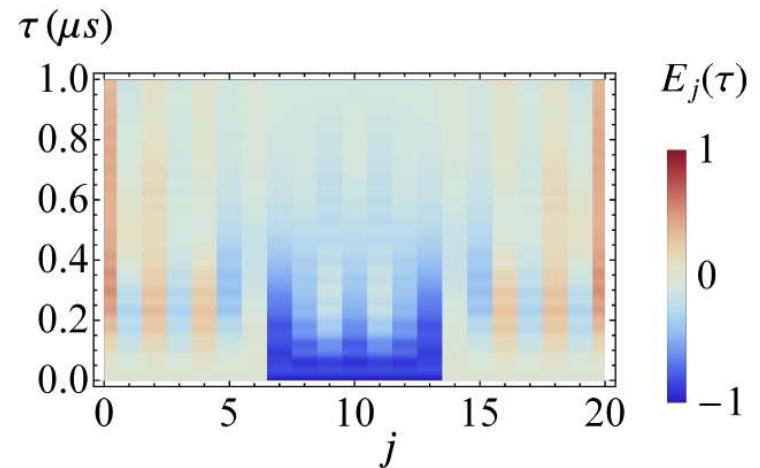
# Quantum simulation of Lattice Gauge Theories



Three atoms represent a link



Rydberg – atom quantum simulation



# Tensor Networks and Matrix Product States

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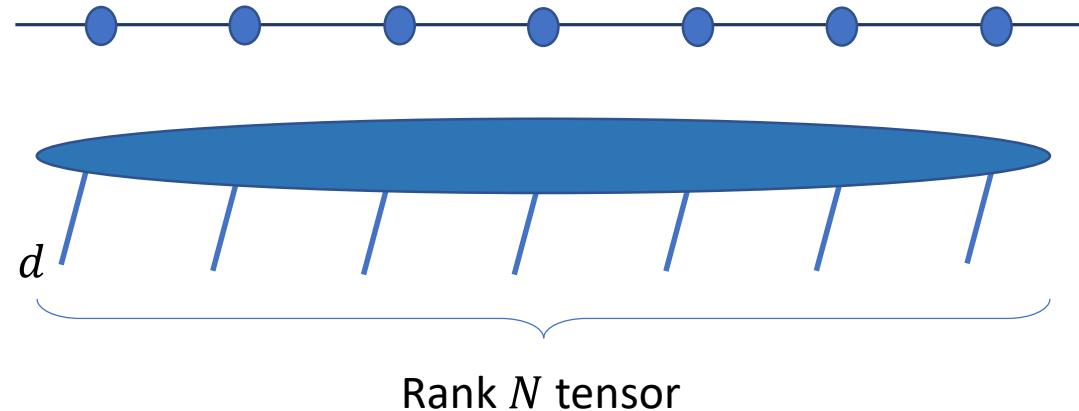
- Efficient method to compress information

# Tensor Networks and Matrix Product States

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- Efficient method to compress information
- Lattice model,  $N$  sites, local dimension  $d \rightarrow \dim \mathcal{H} d^N$

$$|\Psi\rangle = \sum_{\alpha_1, \dots, \alpha_N} c_{\alpha_1, \dots, \alpha_N} |\alpha_1, \dots, \alpha_N\rangle$$

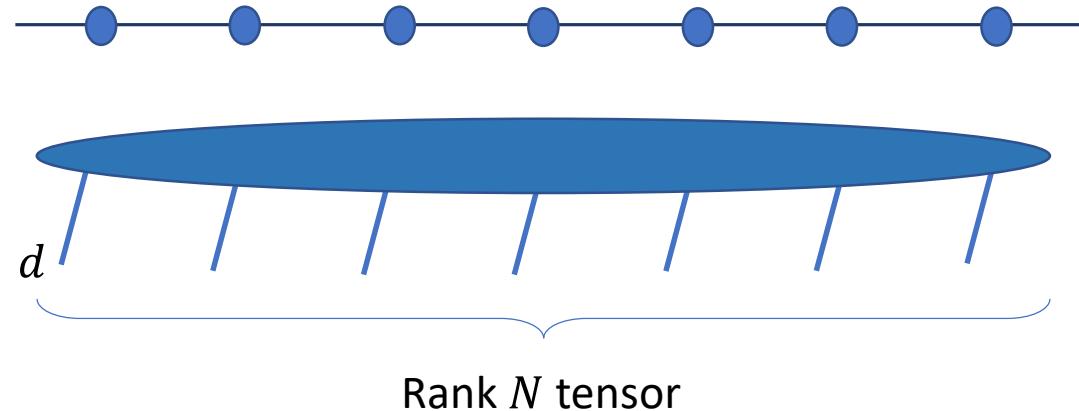


# Tensor Networks and Matrix Product States

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- Efficient method to compress information
- Lattice model,  $N$  sites, local dimension  $d \rightarrow \dim \mathcal{H} d^N$

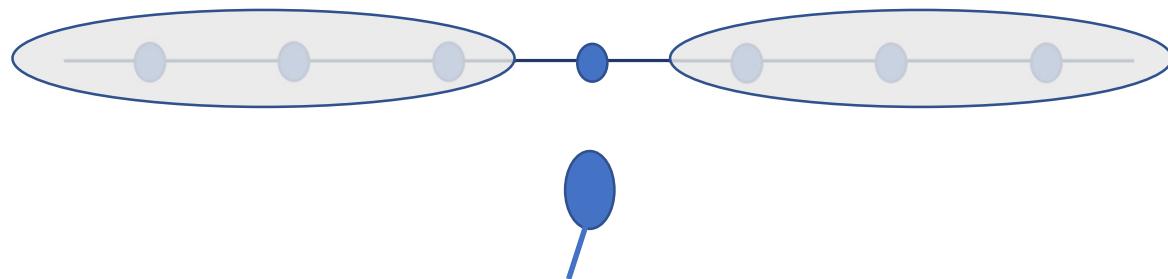
$$|\Psi\rangle = \sum_{\alpha_1, \dots, \alpha_N} c_{\alpha_1, \dots, \alpha_N} |\alpha_1, \dots, \alpha_N\rangle$$



$$\rho_{MF} = Tr[|\Psi\rangle\langle\Psi|]$$

Mean field representation

$Nd$  components for describing each site's state



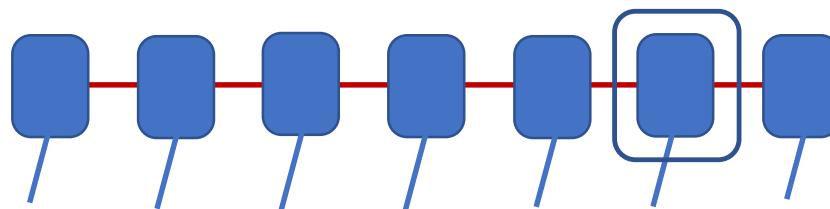
# Tensor Networks and Matrix Product States

---

$$|\Psi\rangle_{MPS} = \sum_{\alpha_1, \dots, \alpha_N} T_{\alpha_1}^{d_1} T_{\alpha_2}^{d_1 d_2} \dots T_{\alpha_{N-1}}^{d_{N-1} d_N} T_{\alpha_N}^{d_N} |\alpha_1, \dots, \alpha_N\rangle$$

Bond dimension  $\chi$ :

- Artificial link
- Allows to keep correlations



Each tensor is a  $d \times \chi \times \chi$  matrix

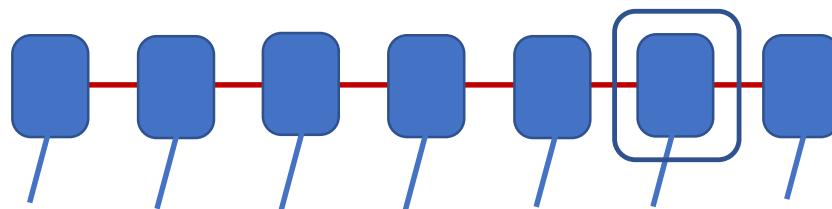
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Given an Hamiltonian  $\hat{H}$ :

- Real time dynamics (Time Evolving Decimation Blocks - TEBD)
- Computing the ground state of: variational ansatz  $\rightarrow \min \langle \Psi | \hat{H} | \Psi \rangle_{MPS}$

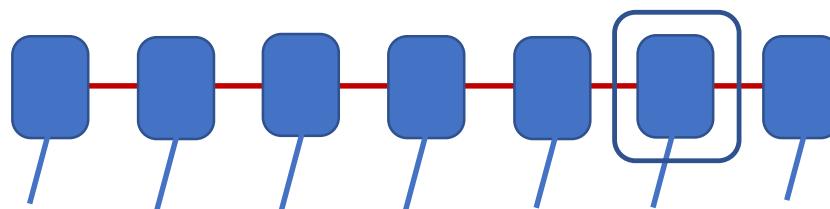
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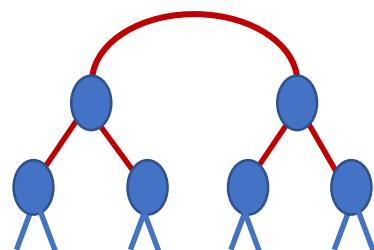
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Different geometries available:

Tree Tensor Networks  
(TTN)



Wave function representation:

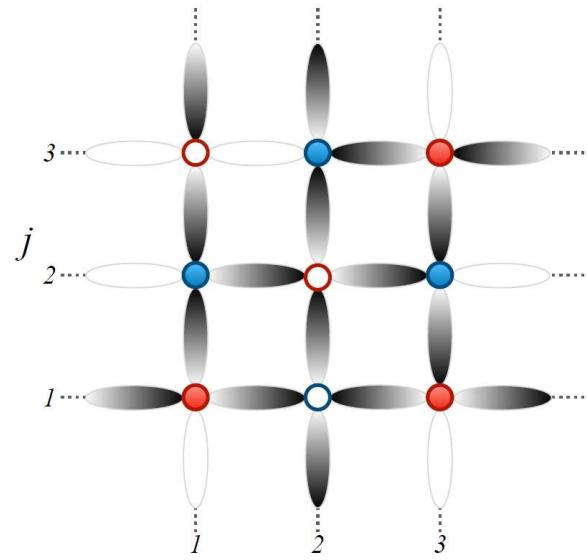
No sign problem  $\rightarrow$

Finite - density simulations are possible

# 2D Abelian lattice gauge theories

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$$\begin{aligned}\hat{H} = & -t \sum_{x,\mu} \left( \hat{\psi}_x^\dagger \hat{U}_{x,\mu} \hat{\psi}_{x+\mu} + h.c. \right) \\ & + m \sum_x (-1)^x \hat{\psi}_x^\dagger \hat{\psi}_x + \frac{g_e^2}{2} \sum_{x,\mu} \hat{E}_{x,\mu}^2 \\ & - \frac{g_m^2}{2} \sum_x \left( \hat{U}_{x,\mu_x} \hat{U}_{x+\mu_x,\mu_y} \hat{U}_{x+\mu_y,\mu_x}^\dagger \hat{U}_{x,\mu_y}^\dagger + h.c. \right)\end{aligned}$$



# 2D Abelian lattice gauge theories

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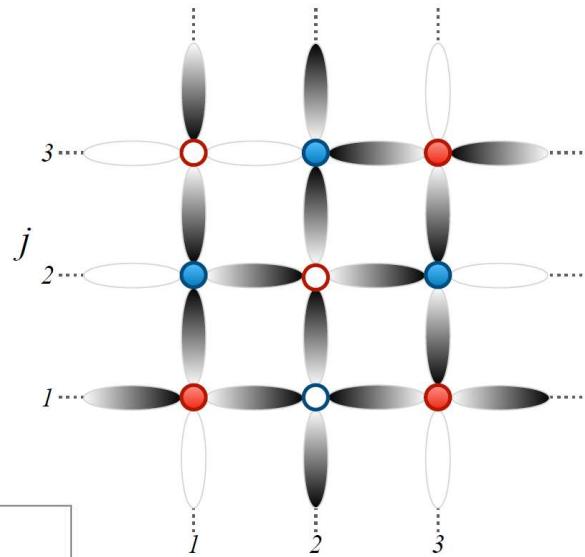
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*Gauge Field*

$$E_{x,\mu_x} = \begin{cases} \text{---} = |\rightarrow\rangle \\ \text{---} = |\emptyset\rangle \\ \text{---} = |\leftarrow\rangle \end{cases}$$

*Matter Field*

$(-1)^{i+j} = +1$	: {	$\textcolor{red}{\circ} = \emptyset$
		$\textcolor{red}{\bullet} = q$
$(-1)^{i+j} = -1$	: {	$\textcolor{blue}{\circ} = \emptyset$
		$\textcolor{blue}{\bullet} = -q$



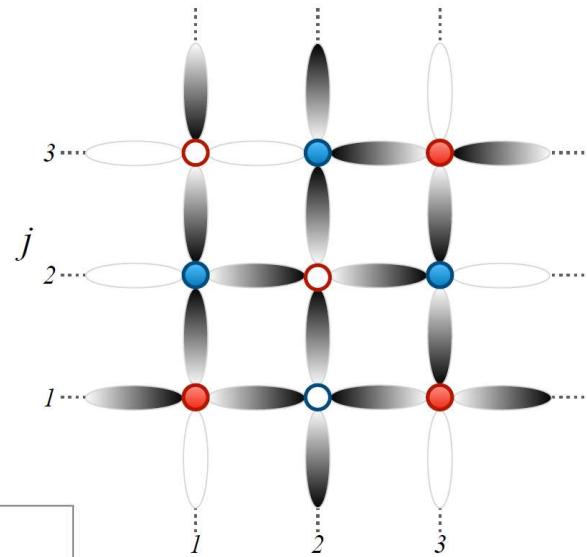
- Truncated electric field
- Staggered matter

# 2D Abelian lattice gauge theories

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Gauge Field	
	$=  \rightarrow\rangle$
	$=  \emptyset\rangle$
	$=  \leftarrow\rangle$

Matter Field	
$(-1)^{i+j} = +1$	: $\begin{cases} \textcolor{red}{\circ} = \emptyset \\ \textcolor{red}{\bullet} = q \end{cases}$
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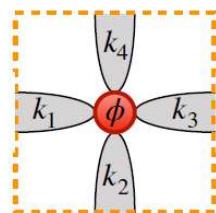


- Truncated electric field
- Staggered matter



Local gauge + matter state:

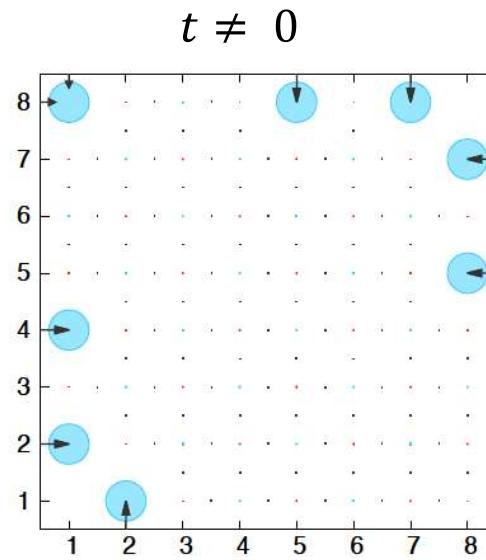
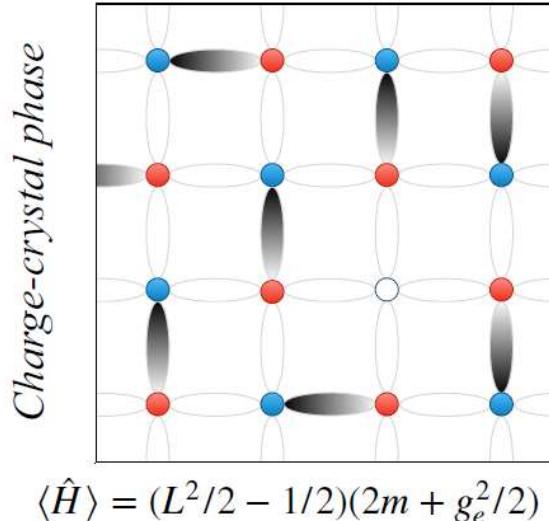
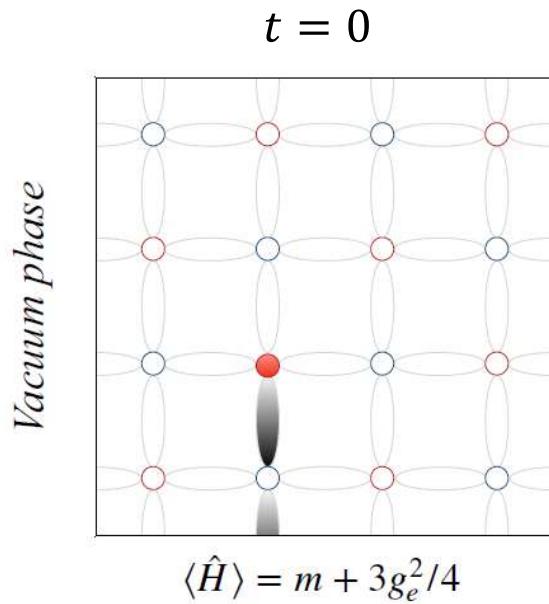
	$=  0,2\rangle$
	$=  1,1\rangle$
	$=  2,0\rangle$



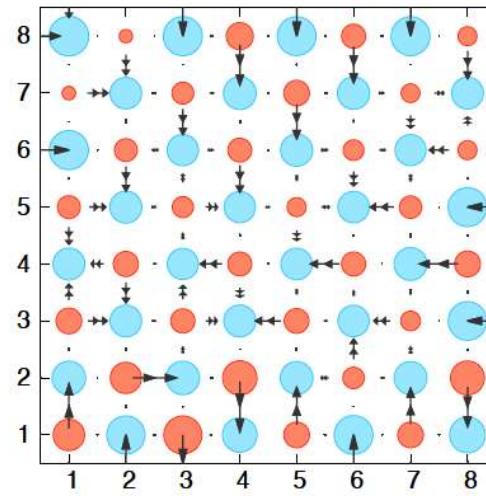
$$= \begin{vmatrix} k_4 & & \\ k_1 & \phi & k_3 \\ & k_2 & \end{vmatrix}$$

T. Felser, P. Silvi, M. Collura,  
S. Montangero. Arxiv: 1911.09693

# 2D Abelian lattice gauge theories



$$m > \frac{g_e^2}{2}$$



# MPS applications

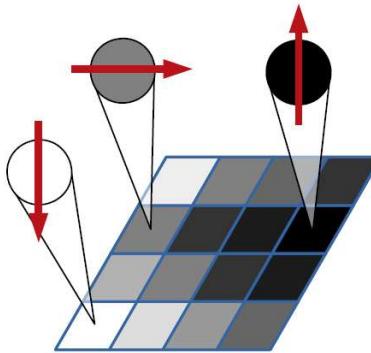
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# MPS applications

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## Machine learning

0 0 0 0 0 0 0 0 0 0 0 0 0 0  
1 1 1 1 1 1 1 1 1 1 1 1 1 1  
2 2 2 2 2 2 2 2 2 2 2 2 2 2  
3 3 3 3 3 3 3 3 3 3 3 3 3 3  
4 4 8 4 4 4 4 4 4 4 4 4 4 4  
5 5 5 5 5 5 5 5 5 5 5 5 5 5  
6 6 6 6 6 6 6 6 6 6 6 6 6 6  
7 7 7 7 7 7 7 7 7 7 7 7 7 7  
8 8 8 8 8 8 8 8 8 8 8 8 8 8  
9 9 9 9 9 9 9 9 9 9 9 9 9 9



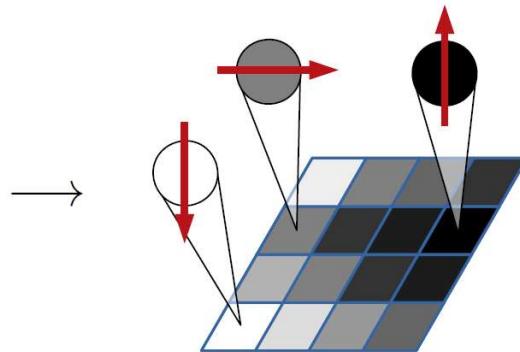
Model	Accuracy
GoogLeNet	93,7%
AlexNet	89,9%
XGBoost	89,8%
<b>MPS</b>	<b>89.0%</b>
2-Layer CNN (Keras)	87.6%

Machine learning: Stoudenmire,  
Quantum Science and Technology 3,  
034003 (2018),  
arXiv:1801.00315 [stat.ML]

# MPS applications

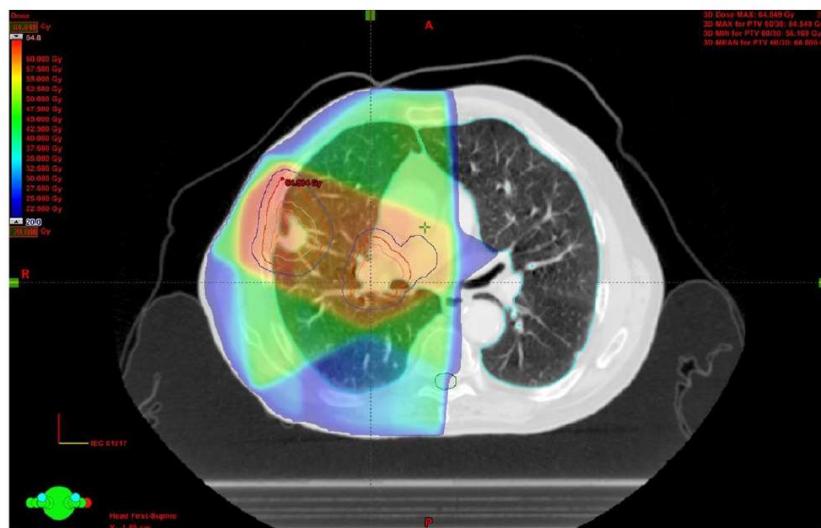
## Machine learning

0 0 0 0 0 0 0 0 0 0 0 0 0 0  
1 1 1 1 1 1 1 1 1 1 1 1 1 1  
2 2 2 2 2 2 2 2 2 2 2 2 2 2  
3 3 3 3 3 3 3 3 3 3 3 3 3 3  
4 4 4 4 4 4 4 4 4 4 4 4 4 4  
5 5 5 5 5 5 5 5 5 5 5 5 5 5  
6 6 6 6 6 6 6 6 6 6 6 6 6 6  
7 7 7 7 7 7 7 7 7 7 7 7 7 7  
8 8 8 8 8 8 8 8 8 8 8 8 8 8  
9 9 9 9 9 9 9 9 9 9 9 9 9 9

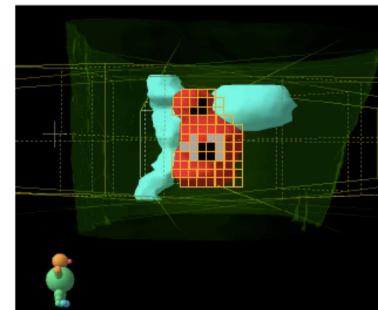


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## Dosing radiation in cancer therapy



Master thesis Samuele Cavinato



S. Montangero



G. Magnifico

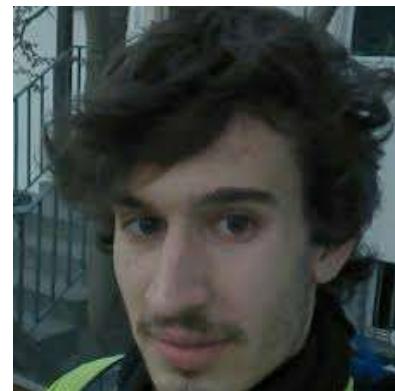


L. Arceci

*Thank you for  
your attention*



T. Felser



M. Rossignolo



M. Collura