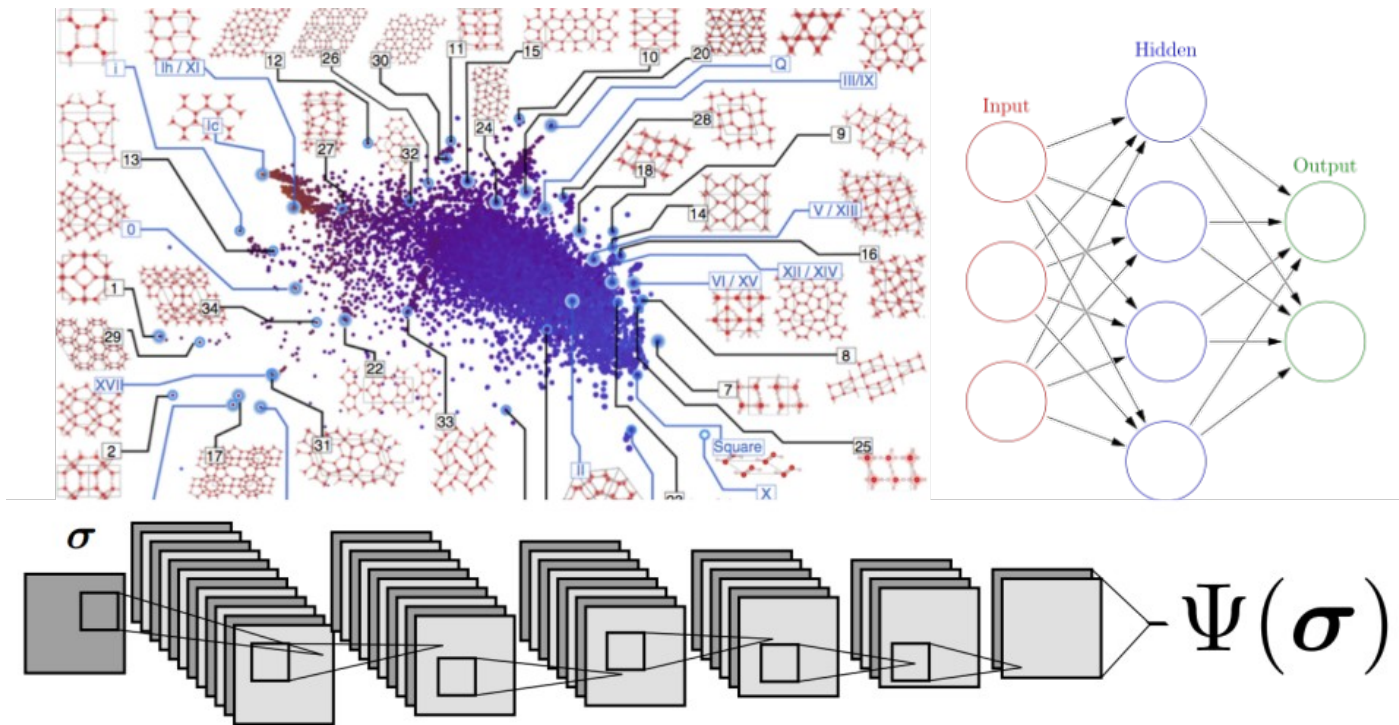


Machine learning in quantum materials



May 24th 2021

Today's learning outcomes

- Some problems in quantum matter can be rephrased so that they can be tackled with AI
- Neural-networks can be used as generic functional approximators

Some paradigmatic examples of machine learning

Supervised
learning



"Dog"

Classification

Unsupervised
learning



Clustering & generation

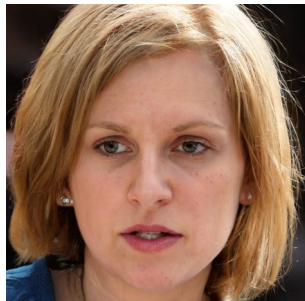
Reinforcement
learning



Decision making

Unsupervised learning

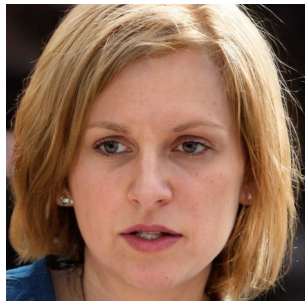
Generating new faces of humans



<https://thispersondoesnotexist.com/>

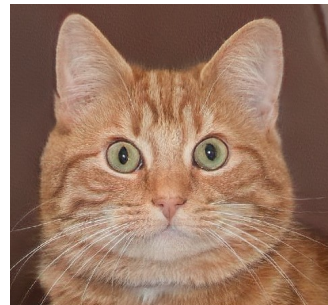
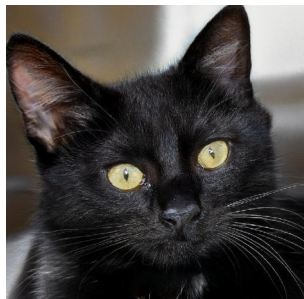
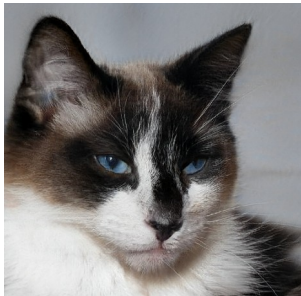
Unsupervised learning

Generating new faces of humans



<https://thispersondoesnotexist.com/>

Generating new faces of cats



<https://thiscatdoesnotexist.com/>

Reinforcement learning



Dancing robots

<https://www.youtube.com/watch?v=fn3KWM1kuAw>

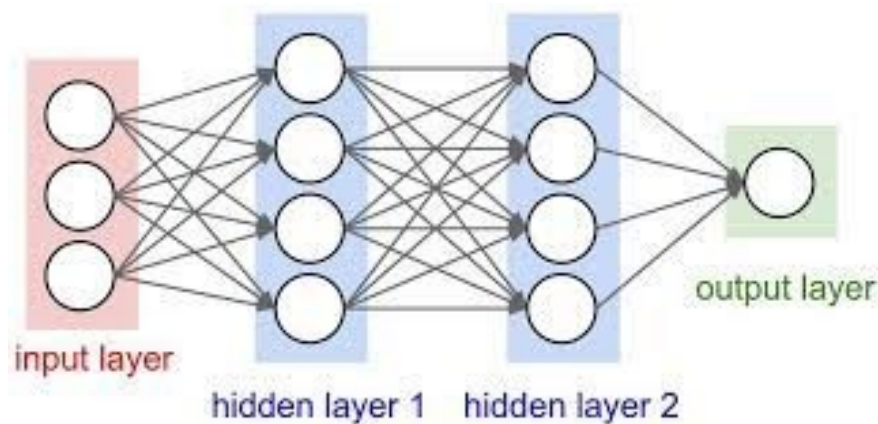
Today's plan

- ML for spontaneous symmetry breaking
- ML for density functional theory
- ML for quantum many-body problems
- Many-body methods for ML

Neural networks

The basics of deep neural networks

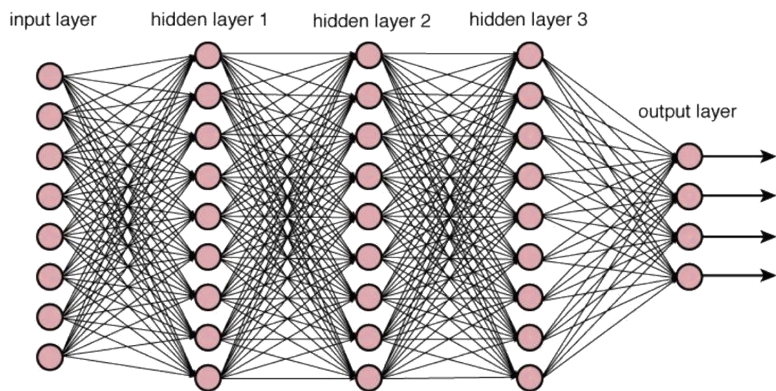
Deep neural networks are “general function approximators”



A deep neural network parametrizes a function of the form $f(\vec{x}) = \vec{y}$

The basics of deep neural networks

Neural networks are a family of parametric functions (bias and weights)



The parameters are optimized to minimize a certain functional

$$\chi = \text{LOSS}[\vec{y}_{\text{real}} - \vec{y}_{\text{predicted}}] = \text{LOSS}[\vec{y}_{\text{real}} - f(\vec{x}_{\text{real}})]$$

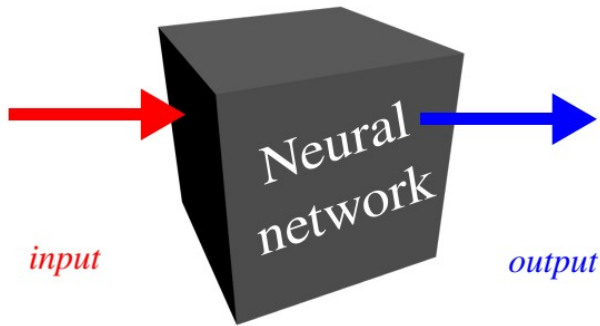
$$\text{For example } \chi \sim |\vec{y}_{\text{real}} - f(\vec{x}_{\text{real}})|^2$$

A simple classification problem

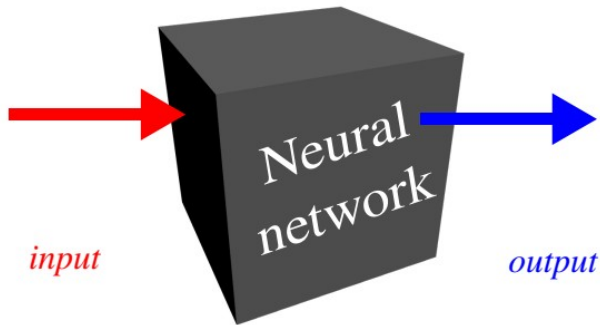


How to distinguish between two different animals with an algorithm?

A simple classification problem



“Cat”

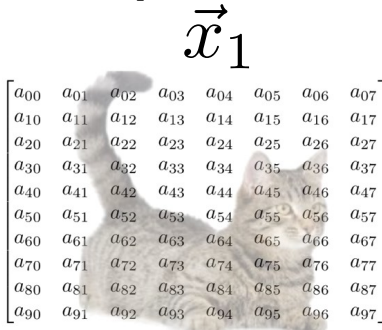


“Dog”

A simple classification problem

If we represent the image as a matrix, we just need to find the right function

\vec{x}_1



a_{00}	a_{01}	a_{02}	a_{03}	a_{04}	a_{05}	a_{06}	a_{07}
a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}	a_{16}	a_{17}
a_{20}	a_{21}	a_{22}	a_{23}	a_{24}	a_{25}	a_{26}	a_{27}
a_{30}	a_{31}	a_{32}	a_{33}	a_{34}	a_{35}	a_{36}	a_{37}
a_{40}	a_{41}	a_{42}	a_{43}	a_{44}	a_{45}	a_{46}	a_{47}
a_{50}	a_{51}	a_{52}	a_{53}	a_{54}	a_{55}	a_{56}	a_{57}
a_{60}	a_{61}	a_{62}	a_{63}	a_{64}	a_{65}	a_{66}	a_{67}
a_{70}	a_{71}	a_{72}	a_{73}	a_{74}	a_{75}	a_{76}	a_{77}
a_{80}	a_{81}	a_{82}	a_{83}	a_{84}	a_{85}	a_{86}	a_{87}
a_{90}	a_{91}	a_{92}	a_{93}	a_{94}	a_{95}	a_{96}	a_{97}

$$f(\vec{x}_1) = \vec{y}_1 = \begin{pmatrix} 1 \\ 0 \end{pmatrix} \quad \text{"Cat"}$$

\vec{x}_2



a_{00}	a_{01}	a_{02}	a_{03}	a_{04}	a_{05}	a_{06}	a_{07}
a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}	a_{16}	a_{17}
a_{20}	a_{21}	a_{22}	a_{23}	a_{24}	a_{25}	a_{26}	a_{27}
a_{30}	a_{31}	a_{32}	a_{33}	a_{34}	a_{35}	a_{36}	a_{37}
a_{40}	a_{41}	a_{42}	a_{43}	a_{44}	a_{45}	a_{46}	a_{47}
a_{50}	a_{51}	a_{52}	a_{53}	a_{54}	a_{55}	a_{56}	a_{57}
a_{60}	a_{61}	a_{62}	a_{63}	a_{64}	a_{65}	a_{66}	a_{67}
a_{70}	a_{71}	a_{72}	a_{73}	a_{74}	a_{75}	a_{76}	a_{77}
a_{80}	a_{81}	a_{82}	a_{83}	a_{84}	a_{85}	a_{86}	a_{87}
a_{90}	a_{91}	a_{92}	a_{93}	a_{94}	a_{95}	a_{96}	a_{97}

$$f(\vec{x}_2) = \vec{y}_2 = \begin{pmatrix} 0 \\ 1 \end{pmatrix} \quad \text{"Dog"}$$

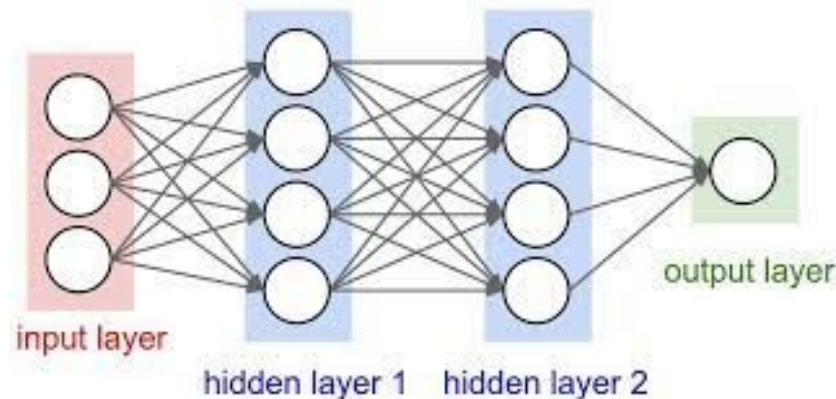
How do we find the function implementing this operation?

Supervised learning in a nutshell

Take a neural-network

Input the image (NxN matrix)

Output a 2D vector

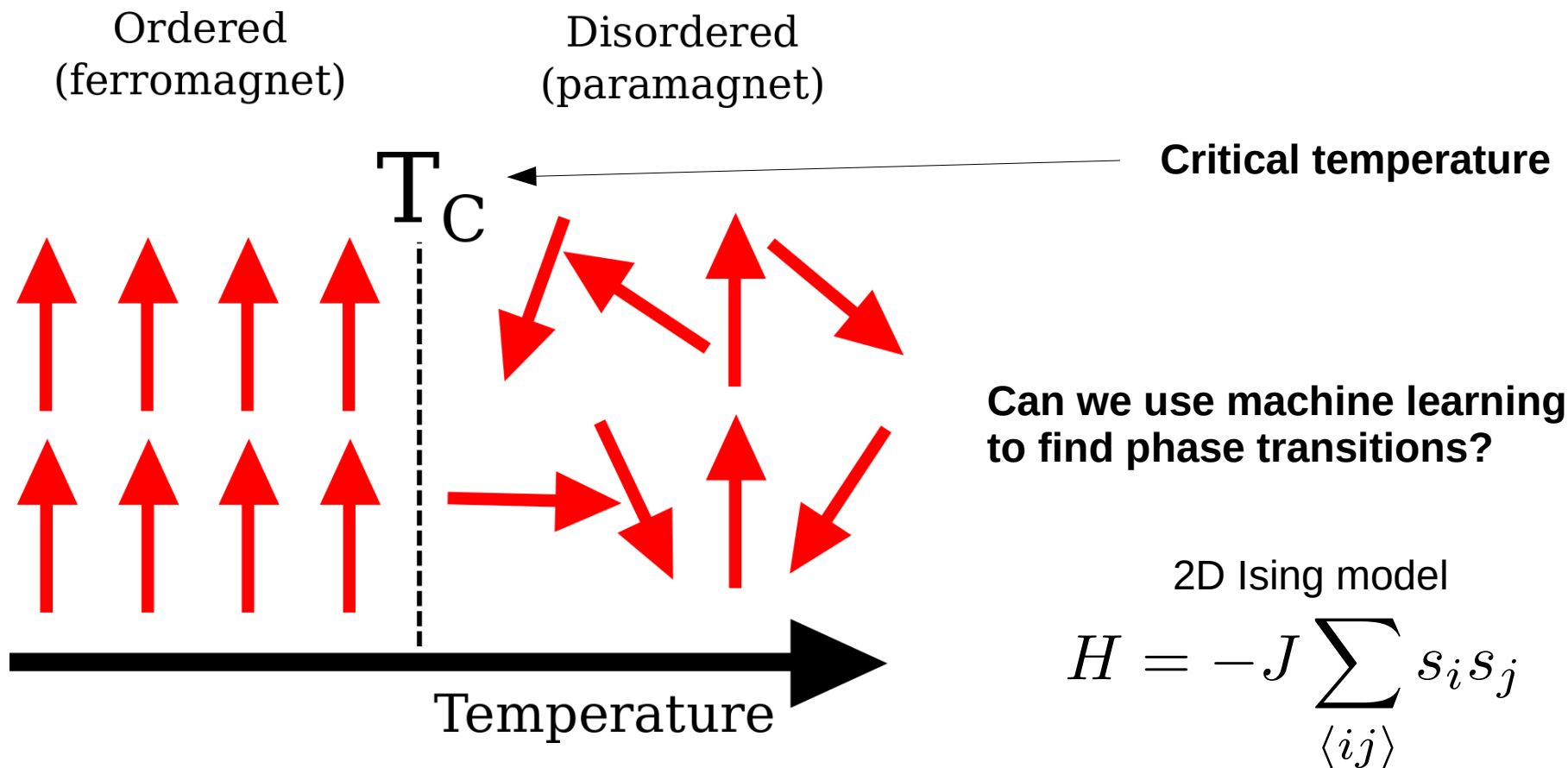


Take a few examples and minimize $\chi = \text{LOSS}[\vec{y}_{\text{real}} - f(\vec{x}_{\text{real}})]$

After the minimization (training), the neural-network will be able to classify new examples

Phase classification

Classical phase transitions



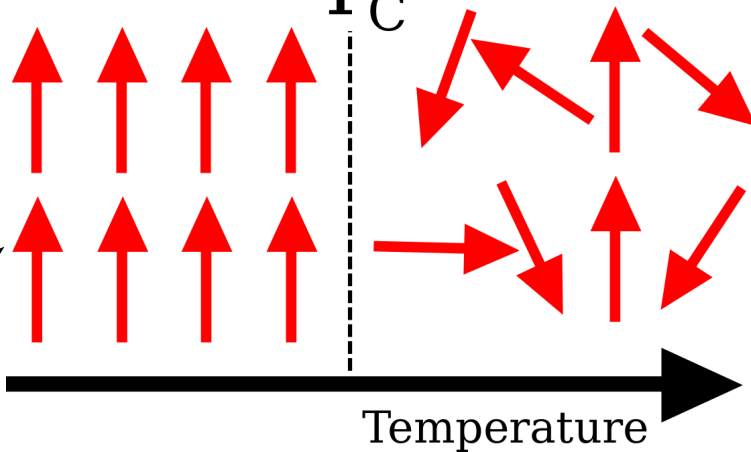
Classical phase transitions

Ordered
(ferromagnet)

Disordered
(paramagnet)

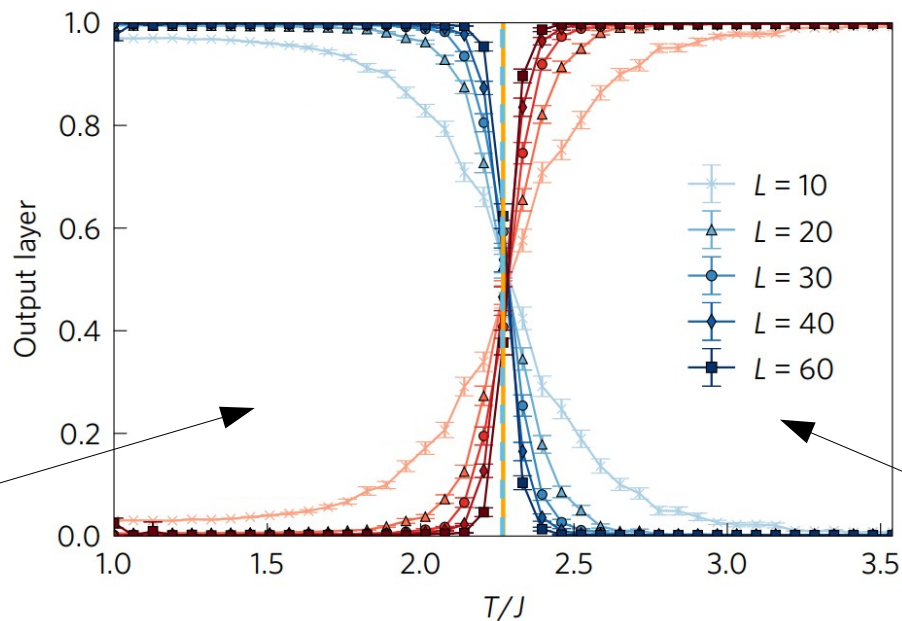
$$H = -J \sum_{\langle ij \rangle} s_i s_j$$

T_C

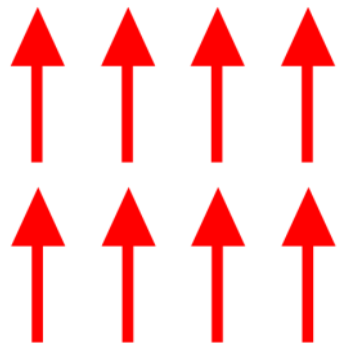


We can use a “classification algorithm” as did before

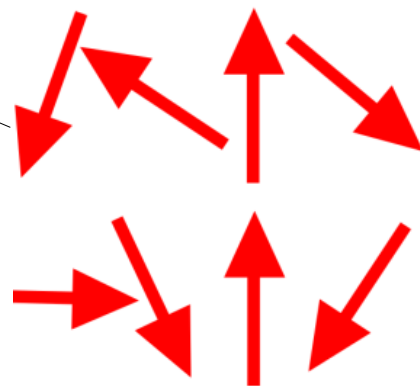
Classical phase transitions



$$H = -J \sum_{\langle ij \rangle} s_i s_j$$



The neural-network learns to classify the two phases



Machine learning in density functional theory

The many-electron problem

The Hamiltonian for electrons in a solid

$$H_{\text{el}} = -\frac{1}{2} \sum_{j=1}^N \nabla_j^2 - \sum_{j=1}^N \sum_{l=1}^M \frac{Z_l}{\tilde{r}_{jl}} + \sum_{j=1}^N \sum_{k>j}^N \frac{1}{r_{jk}},$$

Has an associated electronic density

$$\rho(\mathbf{r}) = N \int d^3\mathbf{r}_2 \cdots \int d^3\mathbf{r}_N |\Psi(\mathbf{r}, \mathbf{r}_2, \cdots, \mathbf{r}_N)|$$

How do we compute the density and energy without computing the many-body wavefunction?

Rminder: The Hohenberg-Kohn theorem

For the ground state of a system, there is a one-to-one relation between the electronic density and the external electrostatic potential

$$H = T + V$$

$$V \leftrightarrow |\Psi\rangle \leftrightarrow \rho_0$$

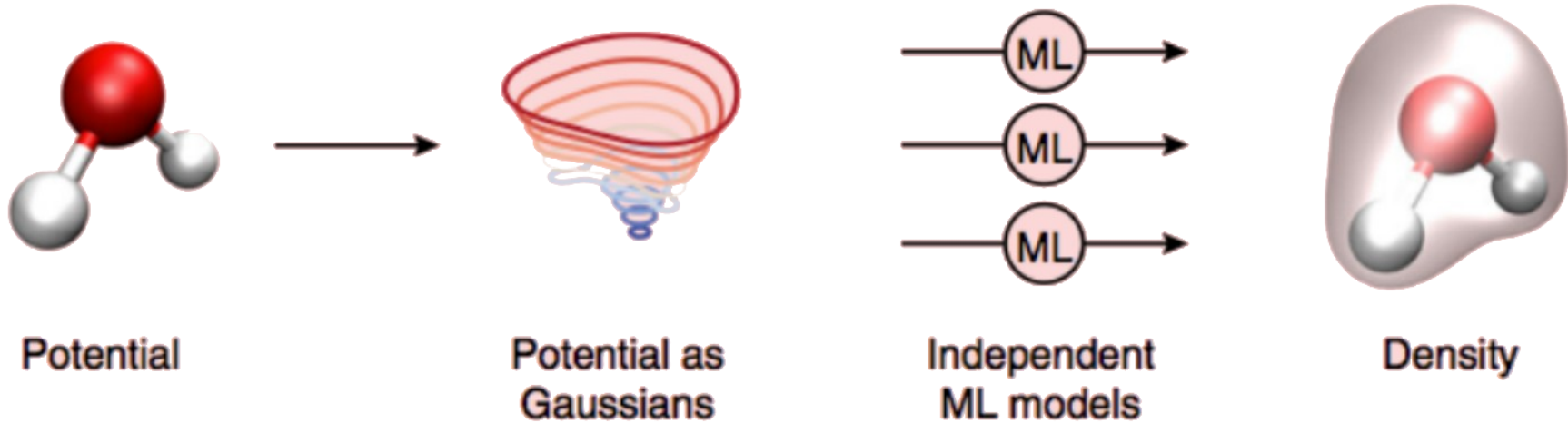
ρ_0 Ground state electronic density

$E[V] \leftrightarrow E[\rho]$ However, we do not know what is the functional

Can we use neural networks to parametrize the functional?

- Machine learning potentials
- Machine learning exchange correlation functional

Machine learning the potential-density functional



The neural network takes as input the potential, and as output the density

Machine learning the exchange-correlation functional

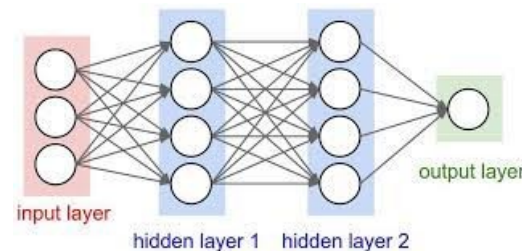
In the Kohn-Sham equations

$$F[\rho] = T[\rho] + J[\rho] + E_{XC}[\rho]$$

The exchange-correlation functional is approximated (LDA, GGA, metaGGA, etc)

Instead of using an approximation, the functional can also be encoded as a neural-network

$$E_{XC} \equiv E_{XC}^{NN}$$
$$\frac{\delta E_{XC}}{\delta \rho} = V_{XC} \equiv V_{XC}^{NN}$$



Neural network quantum states

The quantum many-body problem

Let us go back to a simple many-body problem

$$\mathcal{H} = \sum_{ij} J_{ij} \vec{S}_i \cdot \vec{S}_j$$

And let us imagine that we have L different sites on our system and $S=1/2$

What is the dimension of the Hilbert space?

The quantum many-body problem

Let us go back to a simple many-body problem

$$\mathcal{H} = \sum_{ij} J_{ij} \vec{S}_i \cdot \vec{S}_j$$

And let us imagine that we have L different sites on our system and $S=1/2$

What is the dimension of the Hilbert space?

$$d = 2^L$$

The quantum many-body problem

Let us go back to a simple many-body problem

$$\mathcal{H} = \sum_{ij} J_{ij} \vec{S}_i \cdot \vec{S}_j$$

A typical wavefunction is written as

$$|\Psi\rangle = \sum c_{s_1, s_2, \dots, s_L} |s_1, s_2, \dots, s_L\rangle$$

We need to determine in total 2^L coefficients

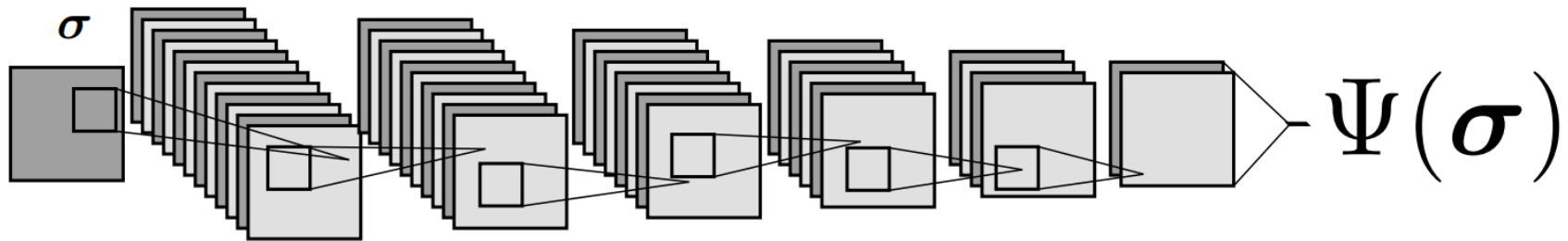
Is there an efficient way of storing so many coefficients?

Neural-network quantum states

Do not store the coefficient, but find the right function that generates them

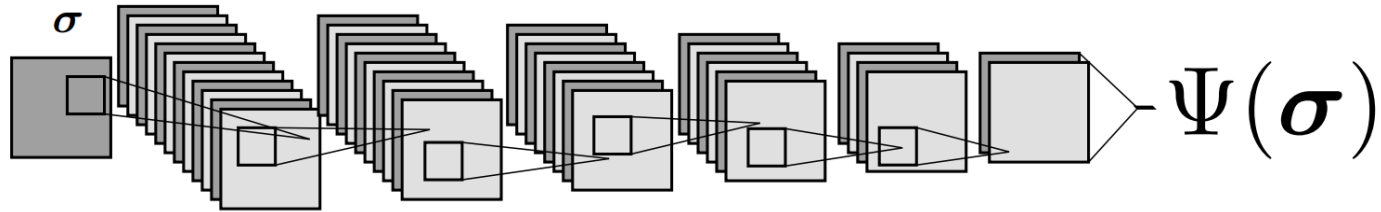
$$c_{s_1, s_2, \dots, s_L} = f(s_1, s_2, \dots, s_L)$$

Deep neural network



The idea is similar as tensor networks, but exploiting a machine-learning architecture

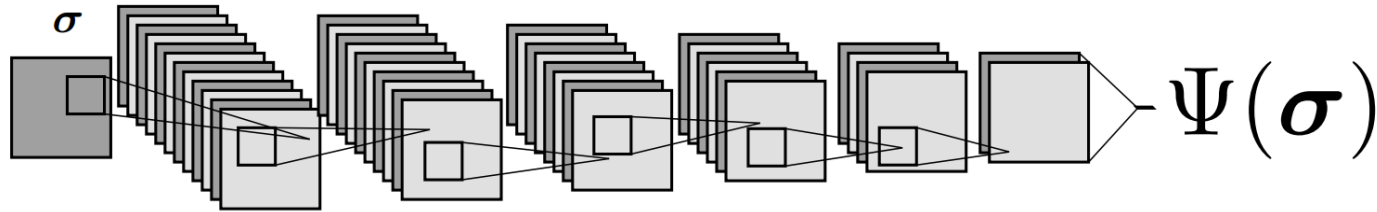
Neural-network quantum states



How do we find the right neural network for the ground state?

$$|\Psi\rangle = \sum c_{s_1, s_2, \dots, s_L} |s_1, s_2, \dots, s_L\rangle \quad c_{s_1, s_2, \dots, s_L} = f(s_1, s_2, \dots, s_L)$$

Neural-network quantum states



How do we find the right neural network for the ground state?

$$|\Psi\rangle = \sum c_{s_1, s_2, \dots, s_L} |s_1, s_2, \dots, s_L\rangle \quad c_{s_1, s_2, \dots, s_L} = f(s_1, s_2, \dots, s_L)$$

Optimize the parameters of the network to minimize

$$E = \frac{\langle \Psi | H | \Psi \rangle}{\langle \Psi | \Psi \rangle}$$

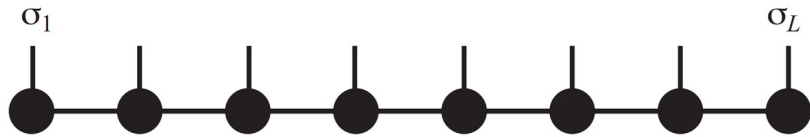
Advantages of neural-network quantum-states

- Not bounded by the area-law (suitable for 2D)
- Can potentially harvest all the power of deep learning
- Can outperform any other quantum many-body method
- Certain architectures are equivalent to tensor-networks

Machine learning with quantum-many body methods

Using a tensor-network to classify images

Tensor-networks allow to parametrize high-dimensional functions

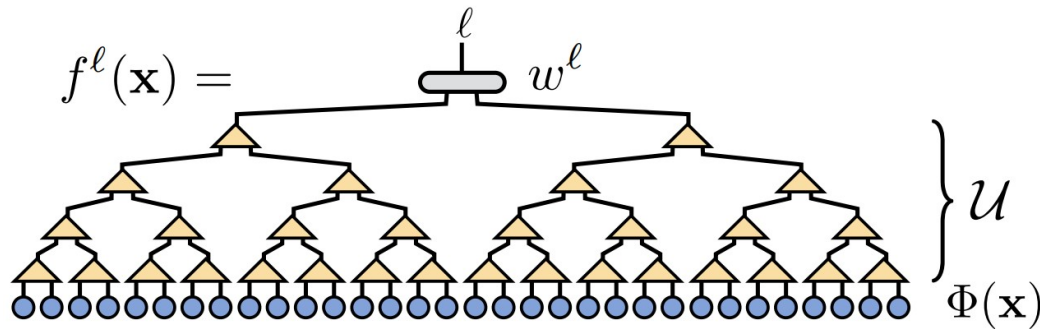


$$c_{s_1, s_2, \dots, s_L} = M_1^{s_1} M_2^{s_2} \dots M_L^{s_L}$$

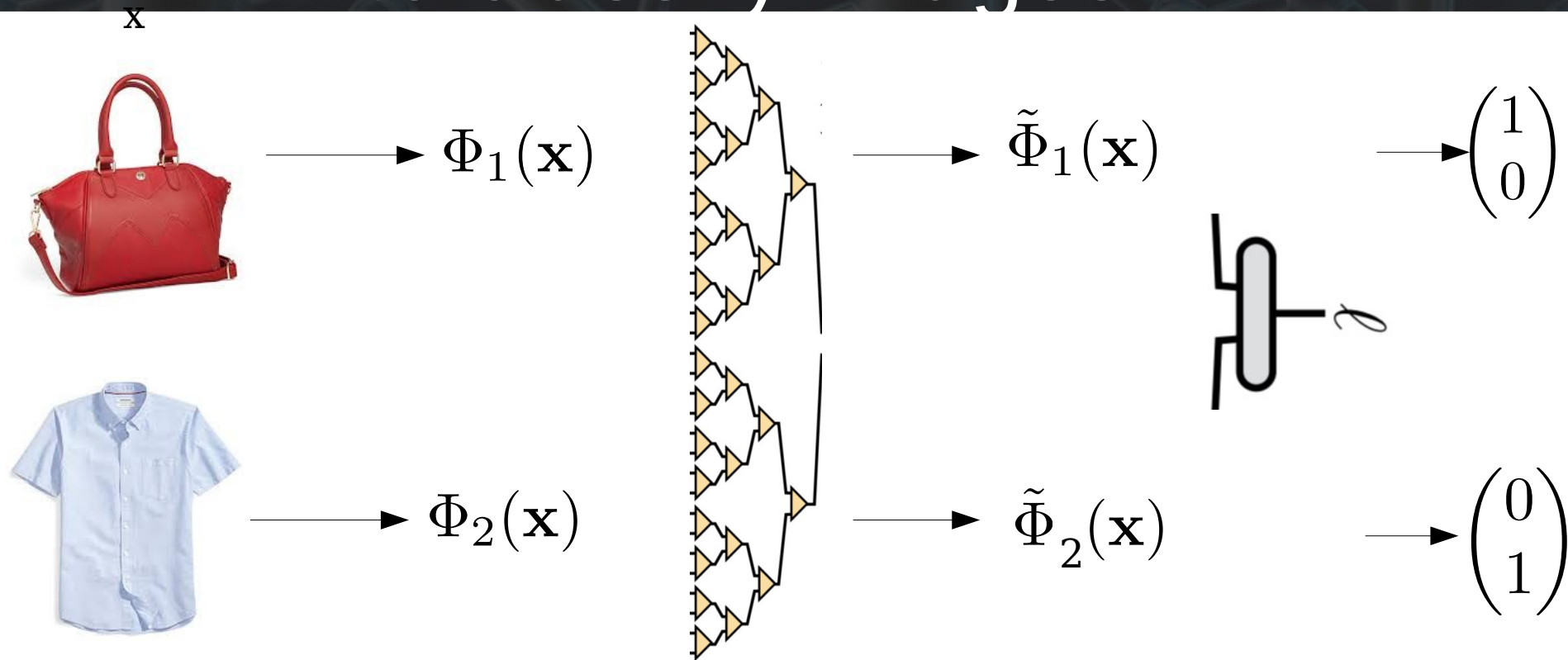
$$|\Psi\rangle = \sum c_{s_1, s_2, \dots, s_L} |s_1, s_2, \dots, s_L\rangle$$

Can we use tensor-network architectures “as if” they were neural networks?

Quantum many-body inspired machine learning



Using a tensor-network to classify images



$$\tilde{\Phi}^{t_1 t_2}(\mathbf{x}_j) = \sum_{s_1, s_2, \dots, s_N} \mathcal{U}_{s_1 s_2 \dots s_N}^{t_1 t_2} \Phi^{s_1 s_2 \dots s_N}(\mathbf{x}_j) .$$

The fashion MNIST dataset classified with tensor-networks



Results

95.38% accuracy in training

88.97% accuracy in testing

Take home

- Machine learning methods can be used to solve some problems in quantum matter
- Neural-networks can be used to parametrize functionals used in quantum physics

Reading material

- Machine learning and the physical sciences, Carleo et al, pages 22-35
- A very interesting course on ML for scientists in

<https://ml-lectures.org/docs/>