

## 11. Artificial intelligence and quantum physics

The learning goals for the last two weeks are:

- \* You know what an artificial neural net is.
- \* You know the difference between supervised and unsupervised learning.
- \* You can give examples of how supervised and unsupervised learning can be used to determine phase transitions.
- \* You know what a restricted Boltzmann machine is.
- \* You can elaborate how such an RBM can be used to represent wave functions

## 11.2 Quantum states from neural nets

Today's lecture is based on the following papers

1. Carleo & Troyer Science 355, 602 (2017)
2. Kousřrřgger et al. Phys. Rev. B 97 195136 (2018)
3. Torlai et al. Nature Phys. 14 447 (2018)

We are going to learn how an artificial neural net can be used to represent a quantum wave-function.

### 11.2.1 Restricted Boltzmann machines

The probability distribution  $q(\{s_i\})$  of  $N$  variables  $s_i$  is unknown but shall be learned from samples drawn from the unknown  $q(\{s_i\})$ .

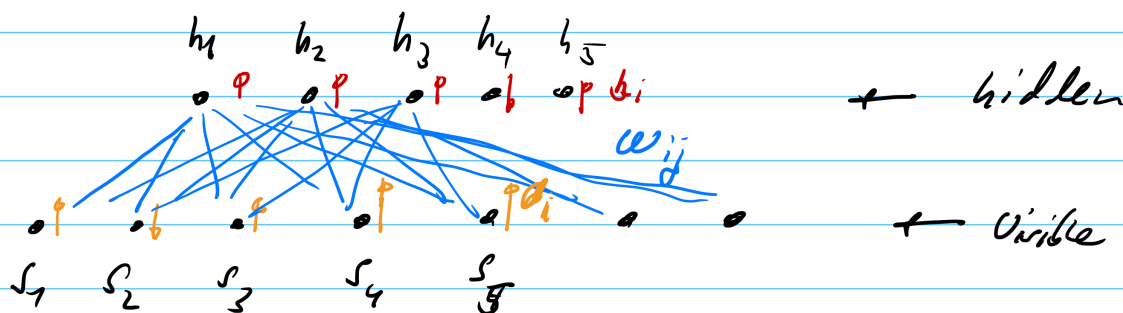
We assume that we can write

$$q(\{s_i\}) \approx p(\{s_i\}) = e^{-E(\{s_i\})}$$

and hence we call it a Boltzmann machine.

Specifically, we write

$$E(\{s_i\}) = \sum_i s_i a_i + \sum_{ij} w_{ij} s_i h_j + \sum_i b_i h_i$$



Our task is to learn  $\{w_{ij}, h_i, a_i\}$  such that

$$p(\{s_i\}) = \sum_{h_i = \pm} e^{-E(\{s_i\})}$$

represents the sampler drawn from  $q(\{s_i\})$  as well a parallel.

A breakthrough came with the use of contrastive divergence by Hinton, which enables an efficient training of the weights. "On contrastive divergence learning" by Carreira-Perpiñán & Hinton.

For quantum wave functions we can do something else. We don't need to rely on samplers (i.e. configurations sampled via Monte-Carlo) but we can capitalize on the fact

that the wave-function itself has a simple cost-function

$$E_{\text{var}} = \frac{\langle \psi_{\vec{w}} | H | \psi_{\vec{w}} \rangle}{\langle \psi_{\vec{w}} | \psi_{\vec{w}} \rangle}$$

This allows us to do an imaginary time evolution

$$|\psi_{\vec{w}}^{\tau}\rangle = e^{-\tau H} |\psi_{\vec{w}}^0\rangle \quad \text{with}$$

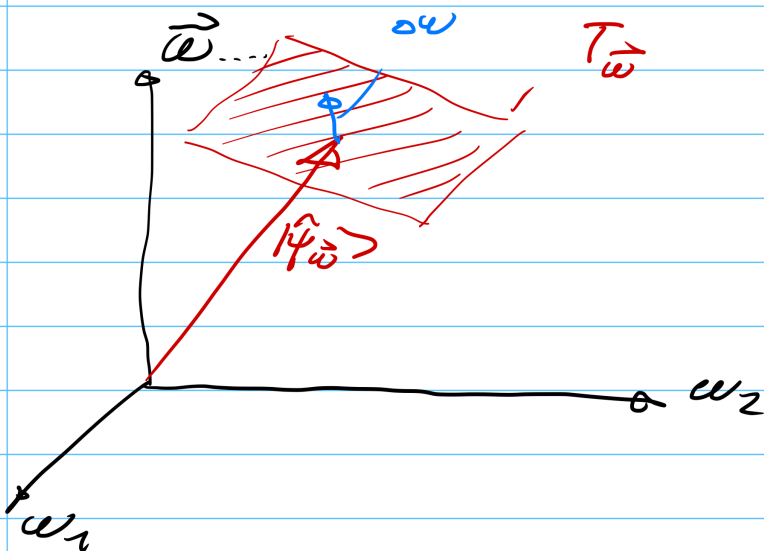
$\tau \rightarrow \infty$  to find the optimal  $\{c_{ij}, h_i, a_i\}$ .

### 11.2.2, Stochastic reconfiguration

We have the normalized wave function

$$|\hat{\psi}_{\vec{w}}\rangle,$$

where  $\vec{w}$  contains all parameters  $\{c_{ij}, h_i, a_i\}$ .



In an update step, we would like to move in the tangent space  $T_{\vec{w}}$  to our current wave function.  $T_{\vec{w}}$  is spanned by

$$|j\bar{\omega}\rangle = |\partial_{\omega_j} \hat{\psi}_{\bar{\omega}}\rangle - |\hat{\psi}_{\bar{\omega}}\rangle \langle \hat{\psi}_{\bar{\omega}} | \partial_{\omega_j} | \hat{\psi}_{\bar{\omega}} \rangle$$

Note, that the  $|j\bar{\omega}\rangle$  are not orthogonal.

We now write

$$|\hat{\psi}_{\bar{\omega}}(t+d\tau)\rangle = e^{-d\tau H} |\hat{\psi}_{\bar{\omega}}(t)\rangle$$

and expand the left-hand side

$$|\hat{\psi}_{\bar{\omega}}(t+d\tau)\rangle \approx |\hat{\psi}_{\bar{\omega}}(t)\rangle + d\tau \sum_{k=1}^{N_{\bar{\omega}}} \bar{\omega}_k(t) \times \\ [|\partial_{\omega_k} \hat{\psi}_{\bar{\omega}}(t)\rangle - |\hat{\psi}_{\bar{\omega}}(t)\rangle \langle \hat{\psi}_{\bar{\omega}}(t) | \\ |\partial_{\omega_k} \hat{\psi}_{\bar{\omega}}(t)\rangle]$$

where we subtracted the last term to ensure we move perpendicular to  $|\hat{\psi}_{\bar{\omega}}(t)\rangle$ .

Expanding also the right-hand side and multiplying from the left with  $\langle j\bar{\omega} |$  we obtain

$$\sum_{k=1}^{N_{\bar{\omega}}} \bar{\omega}_k [\langle \partial_{\omega_j} \hat{\psi}_{\bar{\omega}} | \partial_{\omega_k} \hat{\psi}_{\bar{\omega}} \rangle - \langle \partial_{\omega_j} \hat{\psi}_{\bar{\omega}} | \hat{\psi}_{\bar{\omega}} \rangle \langle \hat{\psi}_{\bar{\omega}} | \partial_{\omega_k} \hat{\psi}_{\bar{\omega}} \rangle]$$

$$= - \langle \partial_{\omega_j} \hat{\psi}_{\bar{\omega}} | H | \hat{\psi}_{\bar{\omega}} \rangle + \langle \partial_{\omega_j} \hat{\psi}_{\bar{\omega}} | \hat{\psi}_{\bar{\omega}} \rangle \langle \hat{\psi}_{\bar{\omega}} | H | \hat{\psi}_{\bar{\omega}} \rangle$$

or

$$\int_{\vec{\omega}} \frac{d\vec{\omega}}{d\tau} = -\vec{F}_{\vec{\omega}}$$

with

$$\int_{\vec{\omega}} = \langle \partial_{\omega_i} \hat{\psi}_{\vec{\omega}} | \partial_{\omega_i} \hat{\psi}_{\vec{\omega}} \rangle - \langle \partial_{\omega_i} \hat{\psi}_{\vec{\omega}} | \hat{\psi}_{\vec{\omega}} \rangle \langle \hat{\psi}_{\vec{\omega}} | \partial_{\omega_i} \hat{\psi}_{\vec{\omega}} \rangle$$

the metric or co-variance tensor and

$$\vec{F}_{\vec{\omega}} = \langle \partial_{\omega_i} \hat{\psi}_{\vec{\omega}} | H | \hat{\psi}_{\vec{\omega}} \rangle - \langle \partial_{\omega_i} \hat{\psi}_{\vec{\omega}} | \hat{\psi}_{\vec{\omega}} \rangle \langle \hat{\psi}_{\vec{\omega}} | H | \hat{\psi}_{\vec{\omega}} \rangle$$

by introducing  $\gamma$  as the imaginary time step we find

$$d\vec{\omega} = -\gamma \int_{\vec{\omega}}^{-1} \vec{F}_{\vec{\omega}}$$

We now need to estimate  $\vec{F}_{\vec{\omega}}$  and  $\int_{\vec{\omega}}$  from Monte-Carlo sampling from

$$\langle \hat{\psi}_{\vec{\omega}} | \hat{\psi}_{\vec{\omega}} \rangle.$$

See Kauerügger et al. Phys. Rev. B 97 195136 (2018) and references therein for the details how to do so.