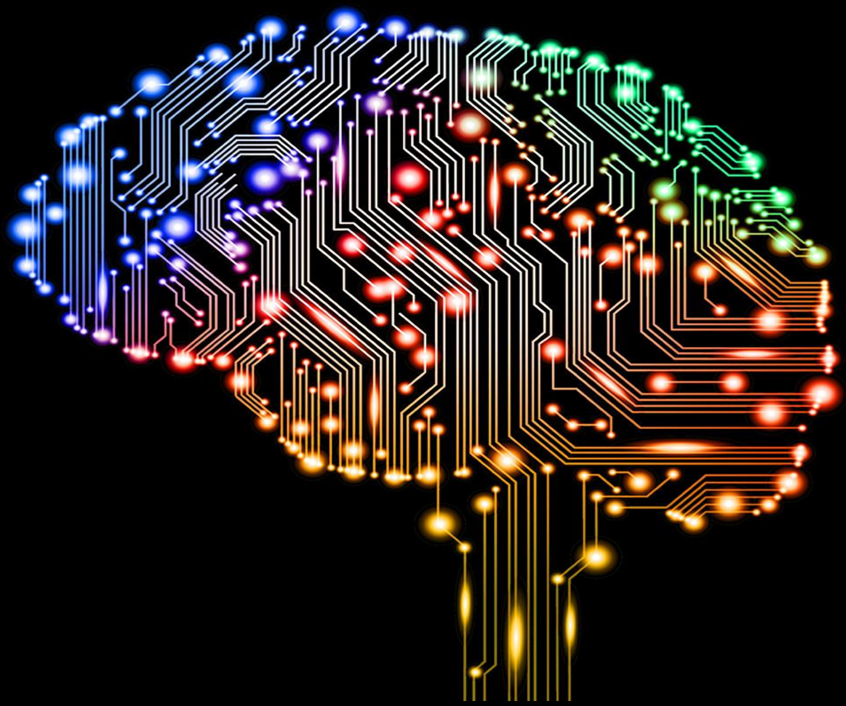
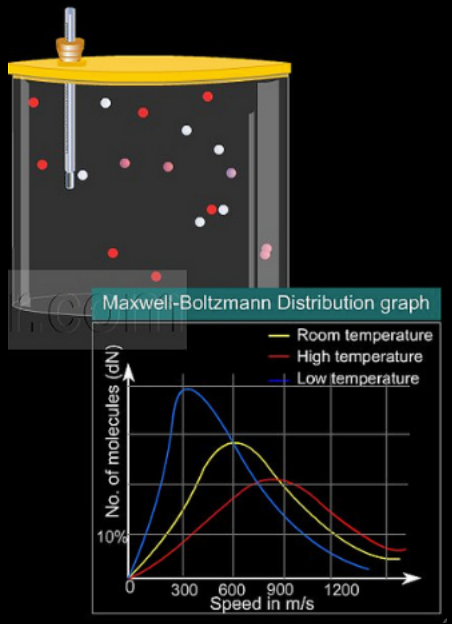
数据驱动的人工智能（6b）基于能量的神经网络

Data Driven Artificial Intelligence

邬学宁 SAP硅谷创新中心
2017 / 03

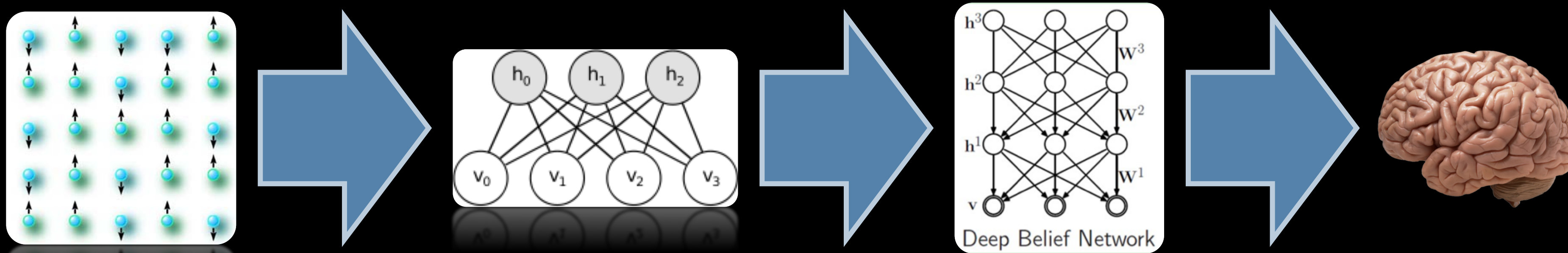


日程: EBN

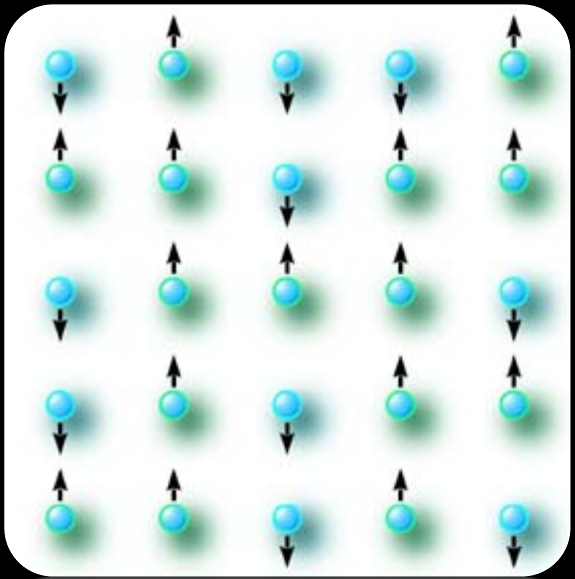


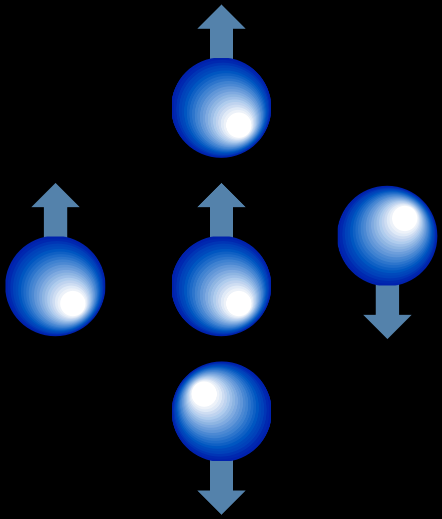
- Bayesian Belief Network
- Auto-encoder / PCA
- Hopfield Network
- Boltzmann Machine
- Restricted Boltzmann Machine
- Deep Boltzmann Machine
- Deep Belief Network
- Sparse Coding
- Game Theory & Generative Adversarial Network

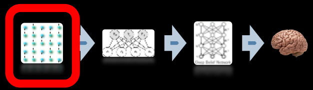
From Ising Model to brain…



The Ising Model (Ernst Ising, 1922)



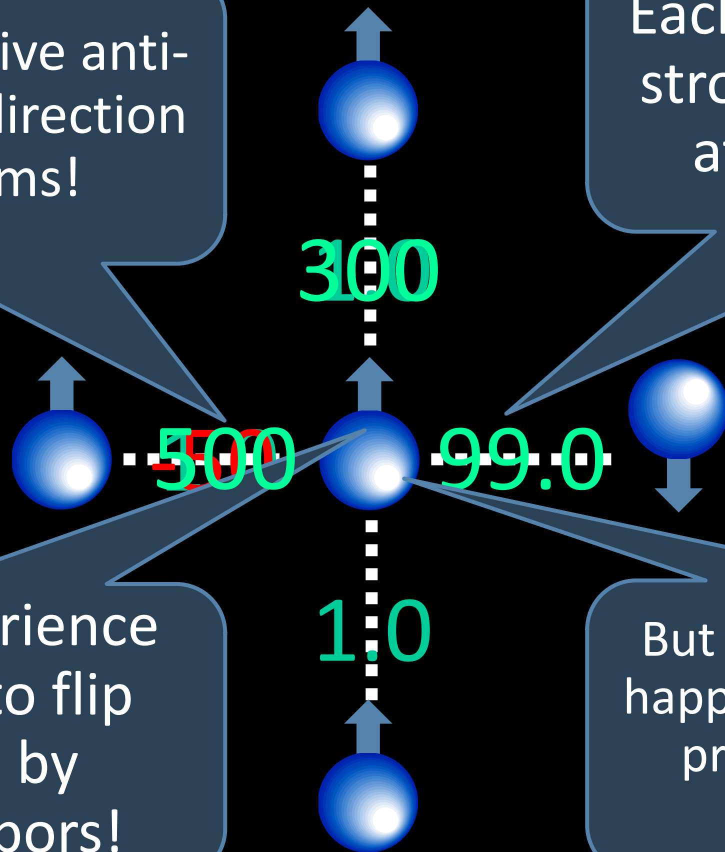




The Ising Model

Negative weights drive anti-correlations in the direction of adjacent atoms!

Each weight indicates how strongly the two adjacent atoms are correlated.

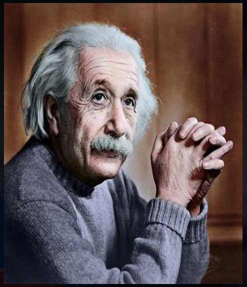


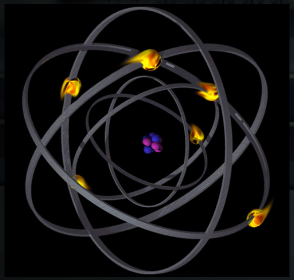
And atoms experience peer-pressure to flip when coaxed by multiple neighbors!

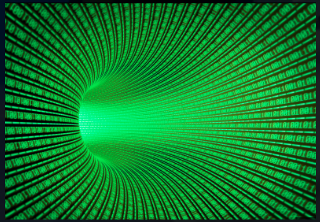
But ultimately, anything can happen – the interactions are probabilistic rather than deterministic!

偏题：人类社会范式转移：从决定论到概率论 / 从原子到比特

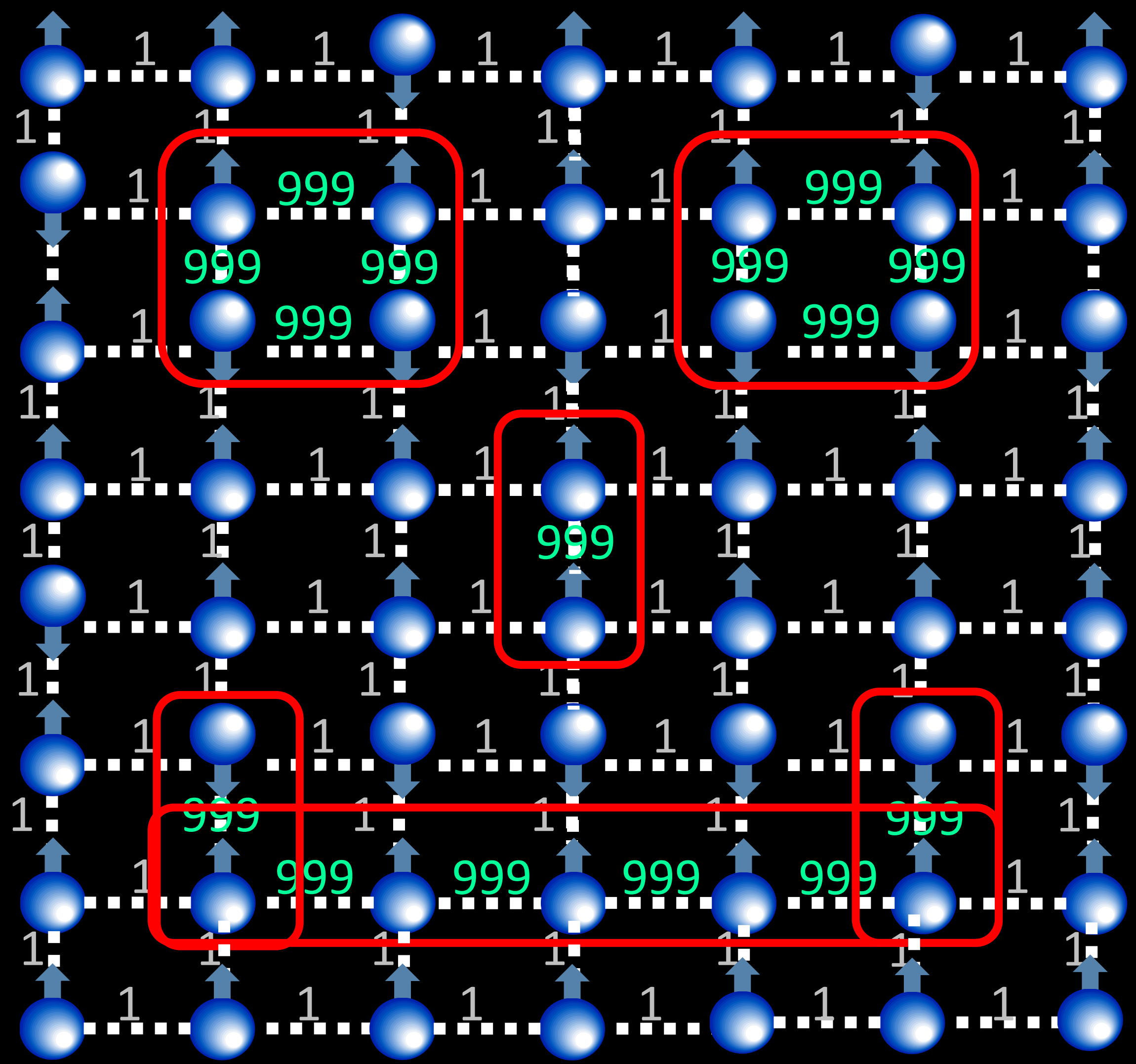
宇宙间，一个技术文明等级的重要标志，是它能够控制和使用的微观维度







Let's See a Simulation!



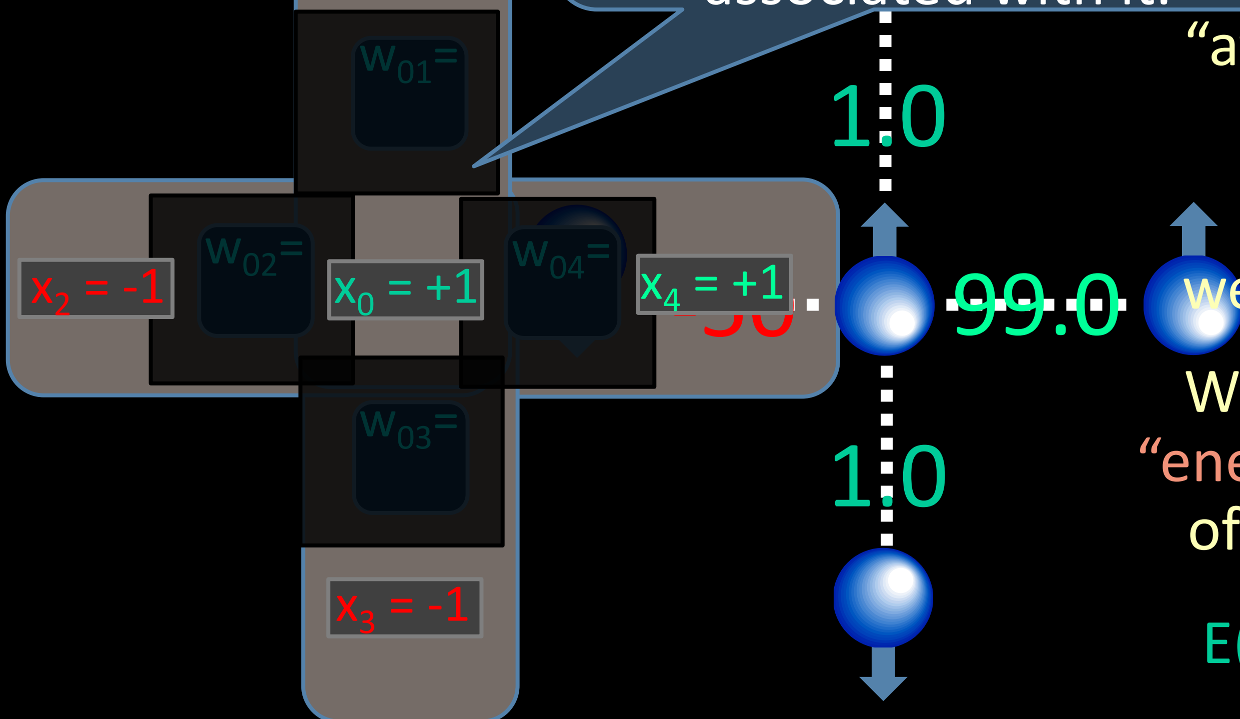
Ising Model Energy

Every configuration of atoms and weights has a specific "energy" associated with it.

…give each up-facing …" a value of $x = +1$

…ve each down-facing "atom" a value of $x = -1$

And between atoms x_i and x_j we'll call the weight w_{ij}.



We can then define the "energy" of a configuration of atoms and weights…

$$E(x,w) = -\sum_{\text{all adjacent pairs } i,j \text{ of atoms}} x_i * x_j * w_{ij}$$

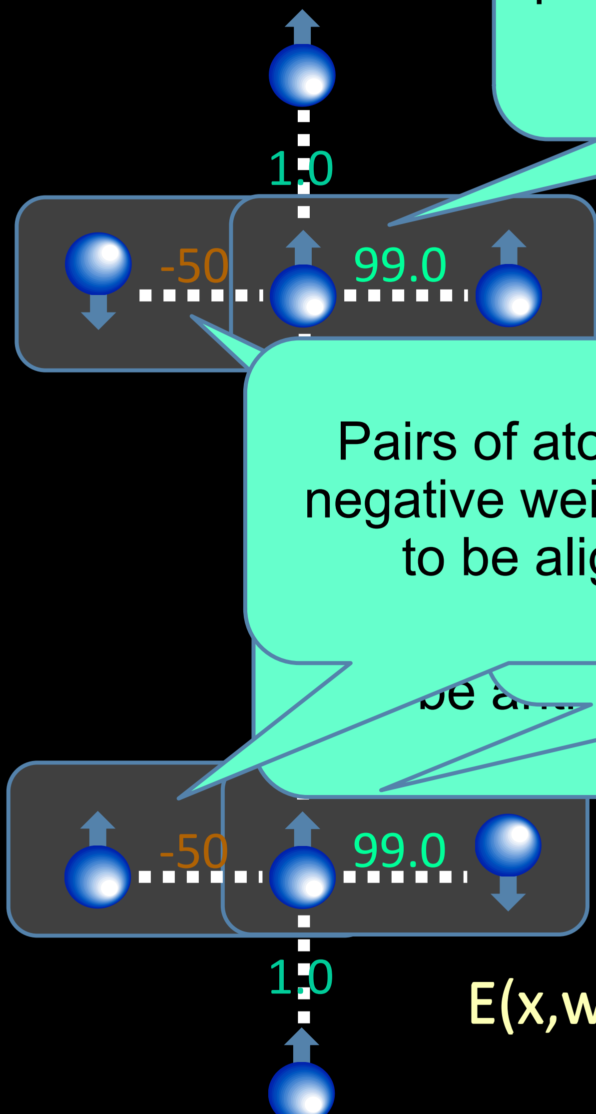
$$E(x,w) = -((1*1*1.0)+(1*-1*-50)+(1*-1*1.0)+(1*1*99))$$

Ising Model Ene

Pairs of atoms with positive weights tend to be aligned.

$$\ldots w) = -\sum x_i * x_j * w_{ij}$$

all adjacent pairs i,j of atoms



Pairs of atoms with negative weights tend to be aligned.

ns with
s tend to
ned.

be a

$E(x,w) = +149$

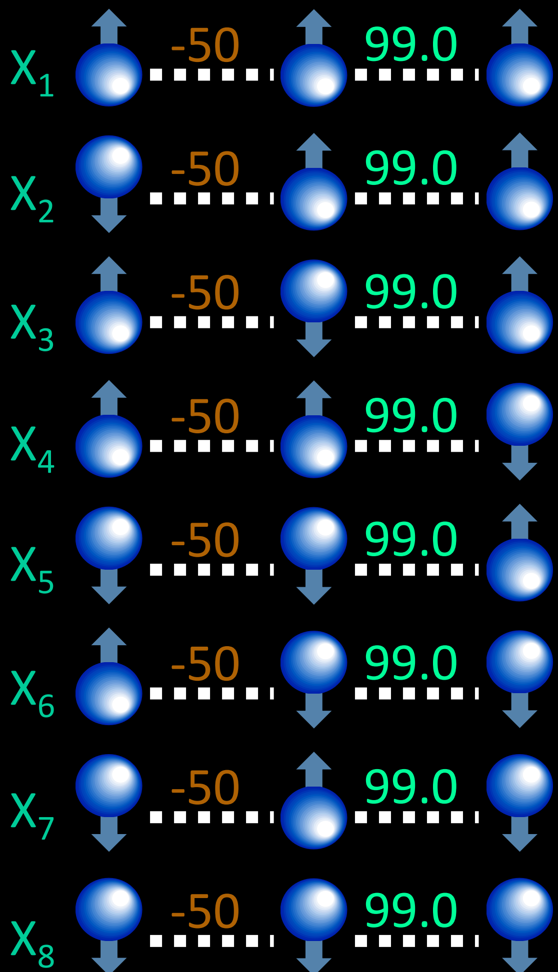
Low-energy configurations are those where atoms connected by positive weights are aligned, and atoms connected by negative ights are anti-aligned.

se configurations tend o be more “stable.”

High-energy configurations are the opposite – their alignment goes against the weights.

These configurations tend to be more “unstable.”

Ising Model Probabilities



$E(x_1,w) = -49$

$E(x_2,w) = -149$

$E(x_3,w) = +49$

$E(x_4,w) = +149$

$E(x_5,w) = +149$

$E(x_6,w) = -149$

$E(x_7,w) = +49$

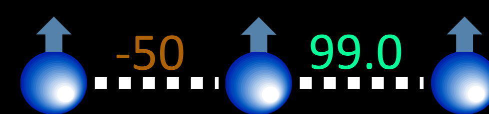
$E(x_8,w) = -49$

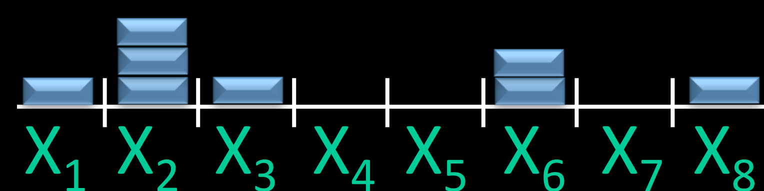
Consider an Ising model with 3 atoms...

There are 2^3 or 8 possible configurations of the atoms.

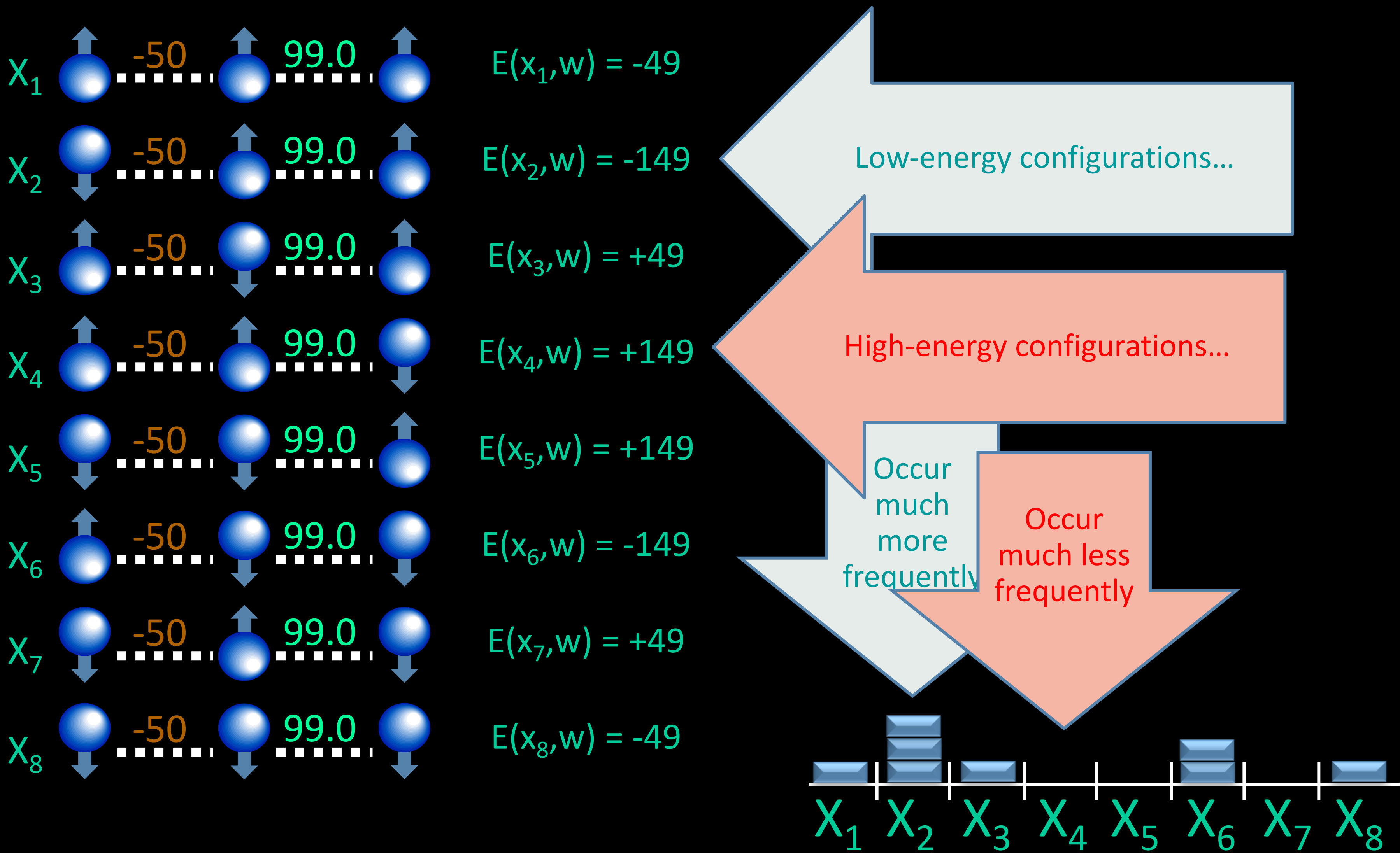
If we let our atoms vibrate (flip up and down) naturally, they will oscillate through these various configurations...

And the probability of a particular configuration occurring depends entirely on the energy of that configuration vs. the energy of all of the other configurations.





Ising Model Probabilities



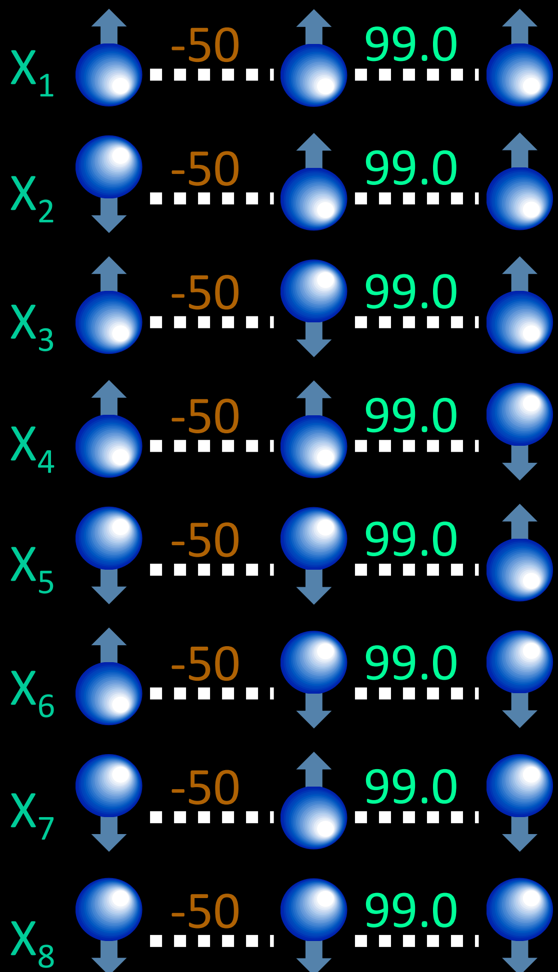
Ising Model Probabi

For simplicity, le ... his
eNRG
f m now o

The bigger the num- erator!

The more negative x_i's energy is…

And thus the higher the probability of the system vibrating to x_i.



$E(x_1$

$E(x_4,w) = +149$

$E(x_5,w) = +149$

$E(x_6,w) = -149$

$E(x_7,w) = +49$

$E(x_8,w) = -49$

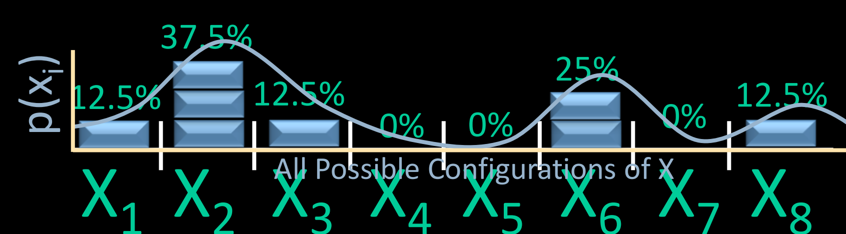
each
ghts w)
d … mula:

$$p(x_i|w) = \frac{e^{-E(x_i,w)}}{\sum_{k=1}^{n} e^{-E(x_k,w)}}$$

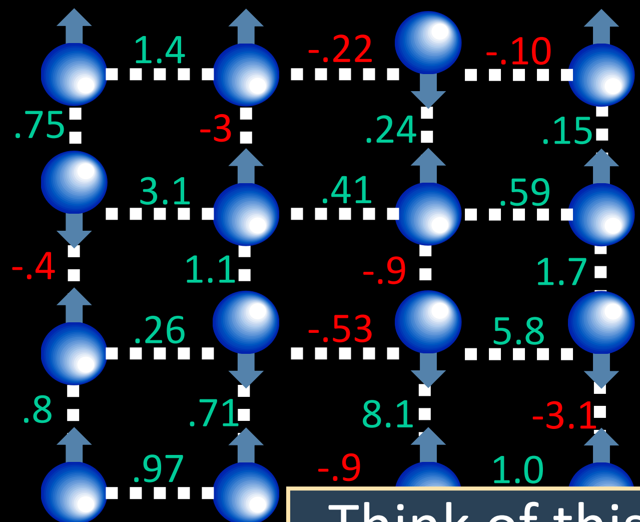
p(the system vibrates to config. x_i) =

$$\frac{\text{eNRG of config. } x_i}{\text{sum of eNRG across all configs}}$$

The probability distribution described by this formula, and shown below, is called a "Boltzmann Distribution".

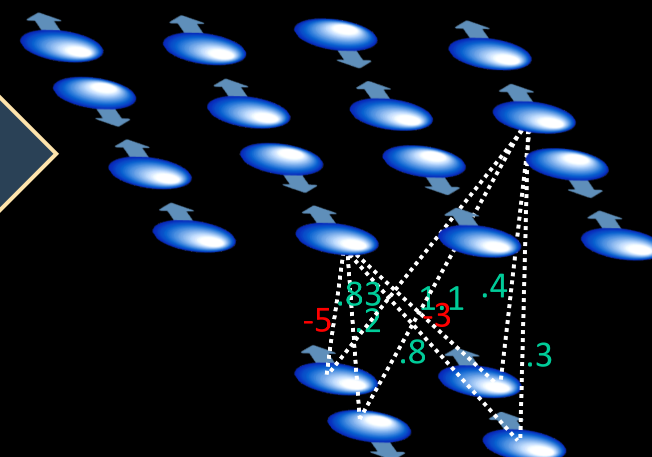


A 3-D Ising Model



Now what if instead of having the weights between adjacent atoms in a plane, we changed things up a bit…

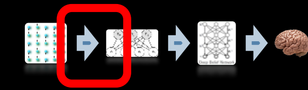
Think of this plane like the pixels on a touch-screen



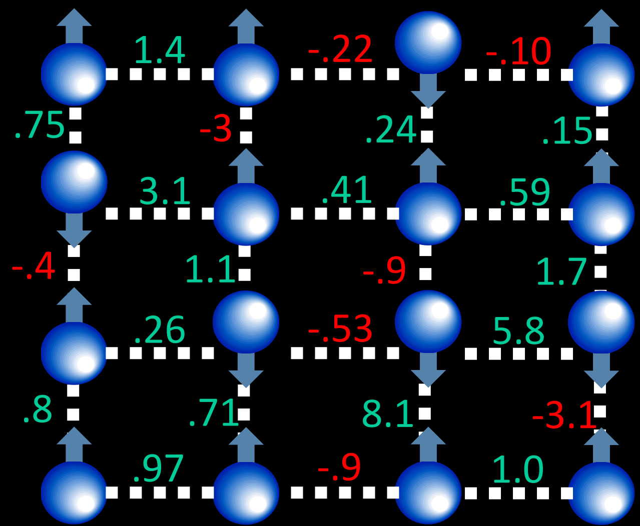
What if we sw
a "visible" plane

In this case, we'll have weights between each atom on the visible plane and every atom on the hidden plane.

Atoms on each plane are now only influenced by the atoms on the other plane.



A 3-D Ising Model

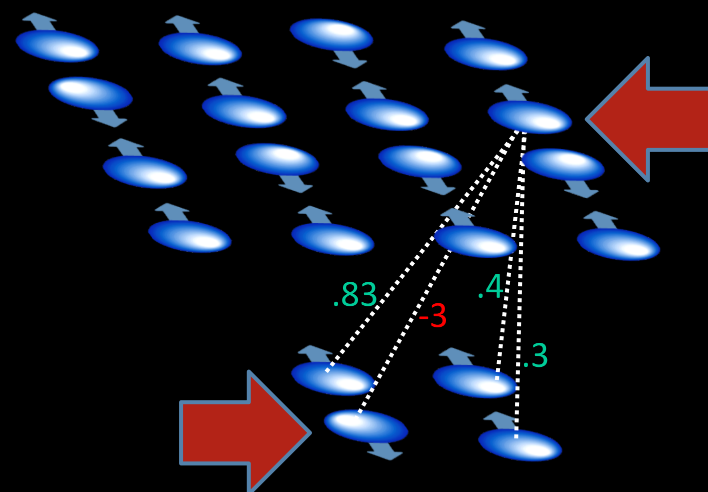


Now what if instead of having the weights between adjacent atoms in a plane, we changed things up a bit…

What if we switched to 2 planes…
a "visible" plane and a "hidden" plane

In this case, we'll have weights between each atom on the visible plane and every atom on the hidden plane.

Atoms on each plane are now only influenced by the atoms on the other plane.



A 3-D Ising Model

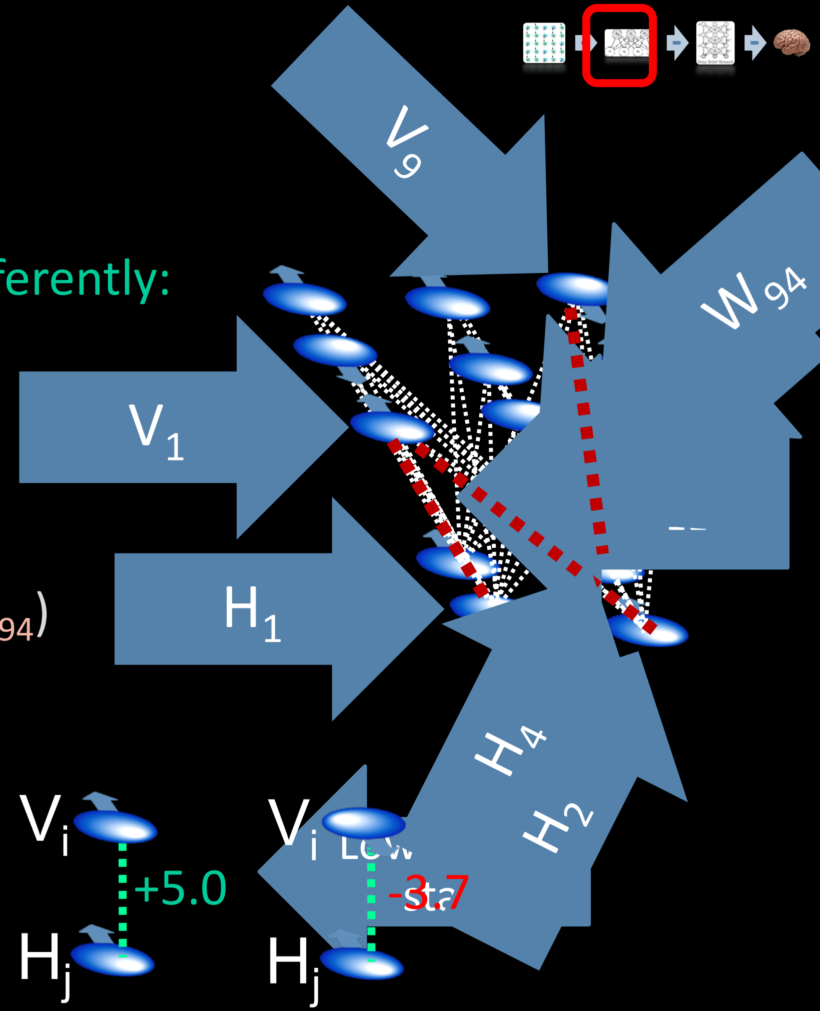
In such a model, energy is computed a bit differently:

$$E(V,H,W) = -\sum_{i=1}^{V} \sum_{j=1}^{H} V_i * H_j * W_{ij}$$

$$= -\left(V_1 * H_1 * W_{11} + V_1 * H_2 * W_{12} + \ldots + V_9 * H_4 * W_{94}\right)$$

Just like before, if we have a visible atom and a hidden atom facing the same direction, connected by a large positive weight, this also contributes to low energy...

And if we have a visible atom and a hidden atom facing the opposite direction, connected by a negative weight, this also contributes to low energy...

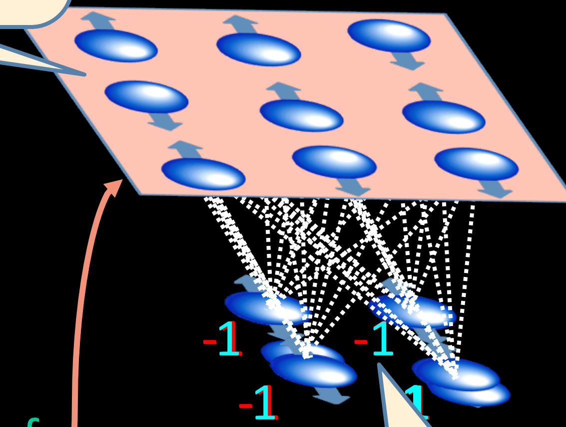


And as before, configurations with lower energy will occur with higher probability than those with higher energy.

A 3-D Ising Mode

"What are the odds that these 9 visible atoms will vibrate to this specific configuration?"

As before, once we ca
we can also find the probability of vibrating



p(the system vibrates to a given 3-D config) =

$$\frac{\text{eNRG of that configuration}}{\text{Total eNRG across all possible configs}}$$

And we can compute the probability of the system vibrating to a specific visual configuration irrespective of what the hidden side looks like…

To do so, we simply sum up the probability of config v showing up for *all* possible hidden configurations:

"Irrespective of what these atoms look like…"

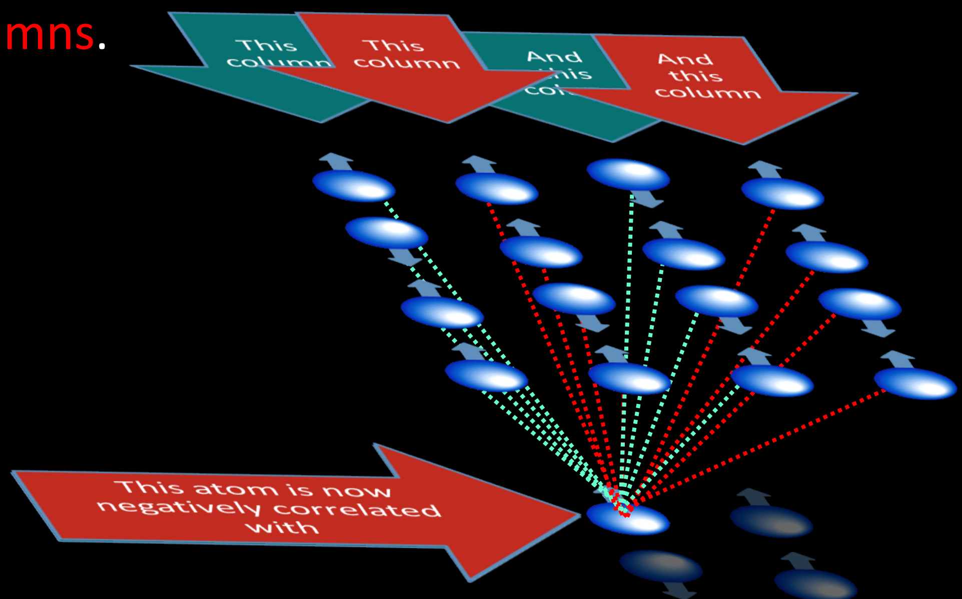
p(the system displays visible config v) =

p(the system displays v when h is {-1,-1,-1,-1}) +
p(the system displays v when h is {-1,-1,-1,1}) +
…
p(the system displays v when h is {1,1,1,1})

A 3-D Ising Model

Just as with our 2-D Ising model,
we can pick weights to bias certain
configurations of atoms.

For instance, we can positively connect the
upper-left hidden atom to odd columns…
and negatively tie it to even columns.



A 3-D Ising Model

Just as with our 2-D Ising model,
we can pick weights to bias certain
configuration

For instance, we can po
upper-left hidden atom
and negatively tie it to even column

We'd now expect our visible layer to
display stripes (o
(off,on,off,on) more
the weights were

But why?

Positively connected visible atoms will likely flip up as well!

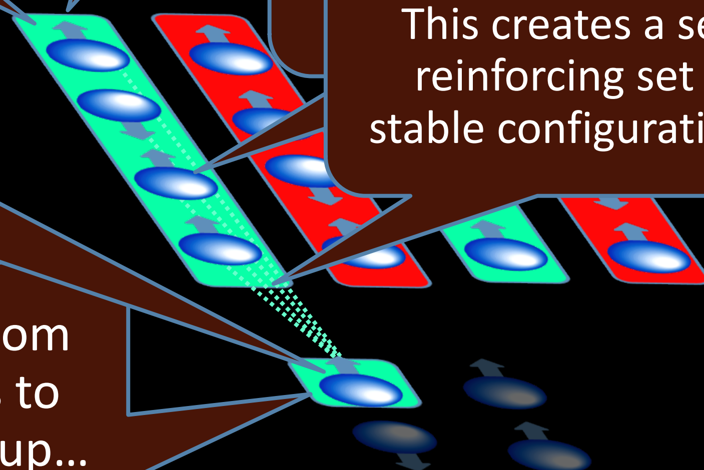
And similarly, if a bunch of visible atoms just happen to randomly flip in a particular direction…

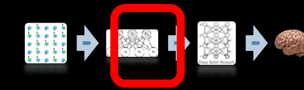
Further reinforcing alignment on the

This creates a self-reinforcing set of stable configurations!

That'll pressure the positively-connected hidden atom to flip too!

If a hidden atom just happens to randomly flip up…





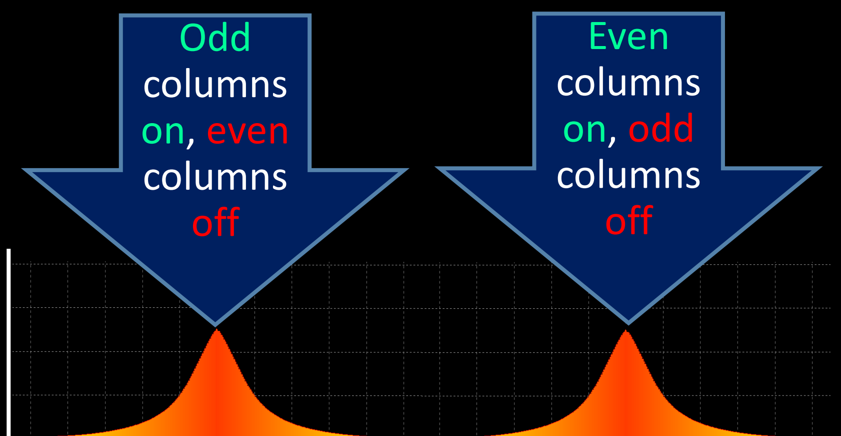
A 3-D Ising Model: A Generative Model

In fact, we say that our 3-D Ising model is "generative".

We call it generative because if we allow the system to vibrate…

it will naturally tend to generate patterns on its visible plane…

based on the specific weights connecting the atoms in the hidden and visible planes.



Boltzmann Distribution
(probability of each configuration occurring)

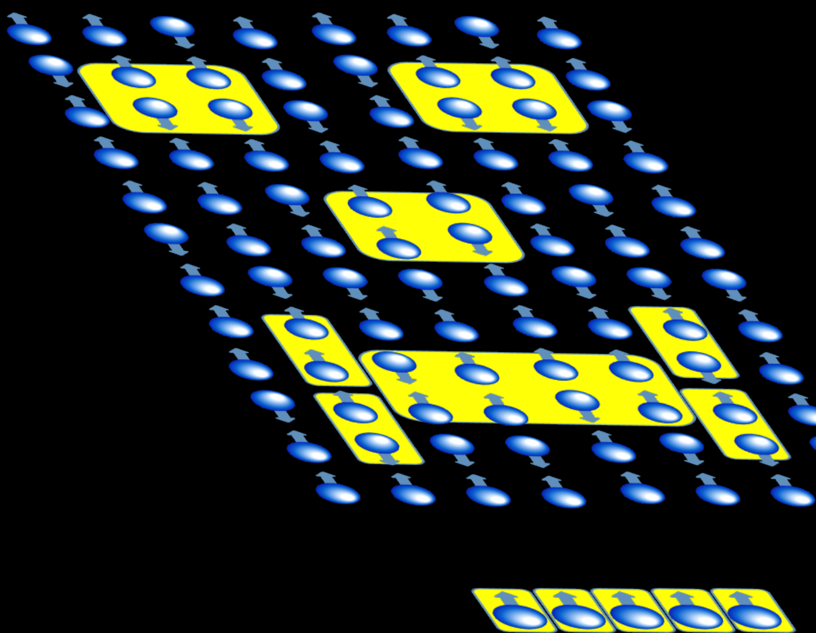
When left to vibrate, it's almost as if the system is daydreaming!

Talking about daydreaming, let's see an example!

A 3-D Ising Model

Here's a demo with 5 atoms in the hidden layer:

Hidden Atom	Has positive weights to …
#1	two sets of "eye" atoms near the top of the visible plane.
#2	a set of "nose" atoms in the middle of the visible plane.
#3	a line of "mouth" atoms in the lower part of the visible plane.
#4	a set of "happy" atoms just above the mouth.
#5	a set of "frown" atoms just below the mouth.



So by manually adjusting the weights between the two planes, we can bias the distribution of what "images" are generated on the visible plane.

An Aha Moment: The 3-D Ising Model becomes the Restricted Boltzmann Machine (RBM)

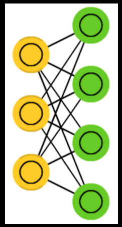
Geoffrey Hinton

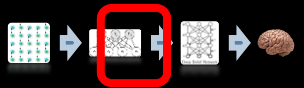
Terry Sejnowski

"Let's use a simulation of an Ising network to encode memories…"

- Approximate quote fabricated by Carey

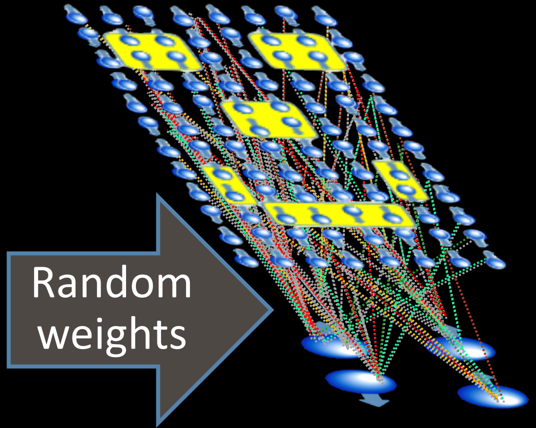
The Restricted Boltzmann Machine
Learning an Image and Daydreaming



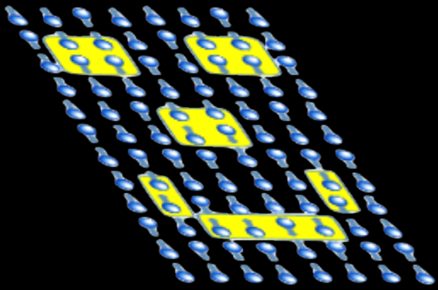


In the early 1980's, Hinton and Sejnowski started experimenting with 3-D Ising Models, also called Restricted Boltzmann Machines (RBMs).

Their goal was to come up with an algorithm that could take a "blank" RBM network…



And teach that network (by modifying its weights) how to "encode" an image…



So if allowed to vibrate, the RBM would vibrate up the encoded image on its visible plane with higher probability than other images…

"I
p

"Right! Then the Ising model will naturally vibrate to our training image more often."

. Well, as we know, an
model naturally vibrates
-energy configurations
frequently than to high-energy ones…"

emember a
cture?"

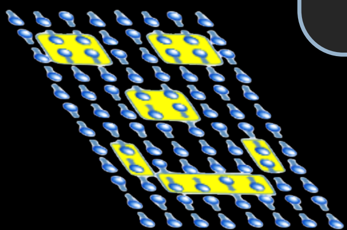
And then find some automated way
Ising model

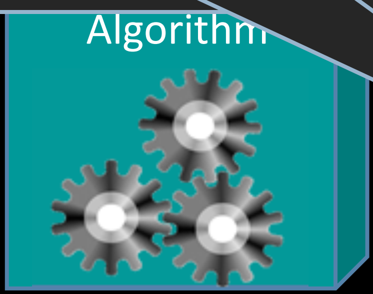
pick a set
uses our
ave as low
ssible."

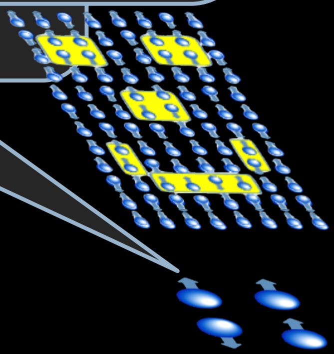
The resulting Ising model is a "generative model!"

Why? Because once it's been trained, if we allow it to vibrate through its natural states, it'll tend to generate the image that it's learned!

rand
es…







Thank you！

As we know, there are known knowns; there are things we know we know. We also know there are known unknowns; that is to say we know there are some things we do not know. But there are also unknown unknowns—the ones we don't know we don't know.

Rumsfeld

Contact information:

Wu Xuening (邬学宁)
SAP硅谷创新中心 首席科学家
A:上海市浦东新区晨辉路1001号
E: x.wu@sap.com
T:021-61085287