

Advanced Monte Carlo algorithms

Bad Honnef Physics School

Computational Physics of Complex and Disordered Systems

Werner Krauth

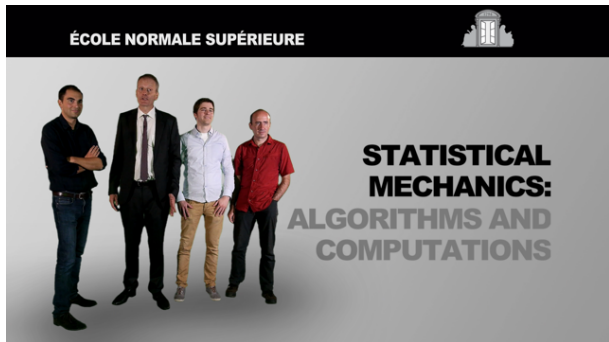
Département de Physique
Ecole Normale Supérieure, Paris, France

23 September 2015

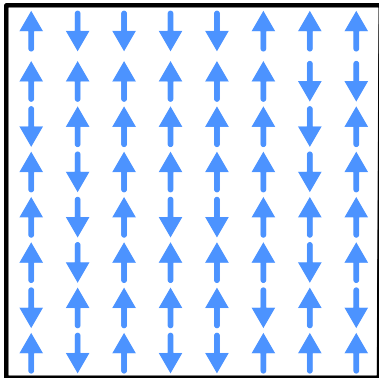
- Monte Carlo algorithms - basic notions.
- Hard disks: From detailed balance to global balance and to cluster algorithms.
- Integration and Sampling: From Gaussians to Maxwell and Boltzmann.
- **Cluster algorithms for spin models: Ising, XY, Spin glasses.**



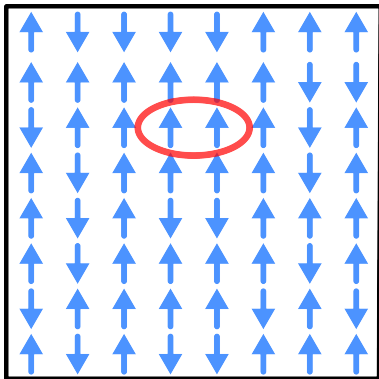
MOOC Statistical Mechanics: Algorithms and Computations



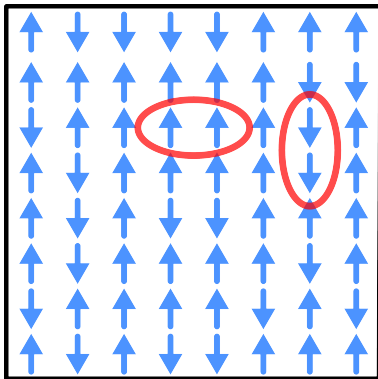
- see also: Werner Krauth *Statistical Mechanics: Algorithms and Computations* (Oxford, 2006)



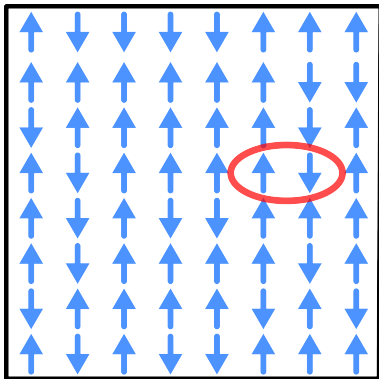
- spins $\sigma = \pm 1$



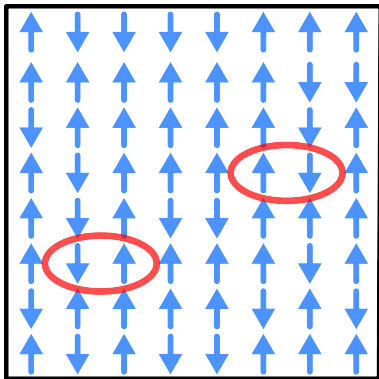
- pair energy $E_{ij} = -1$



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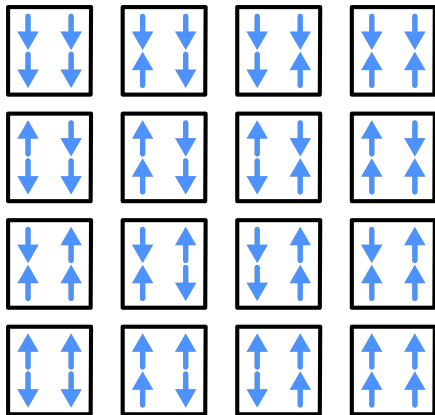


- pair energy $E_{ij} = +1$

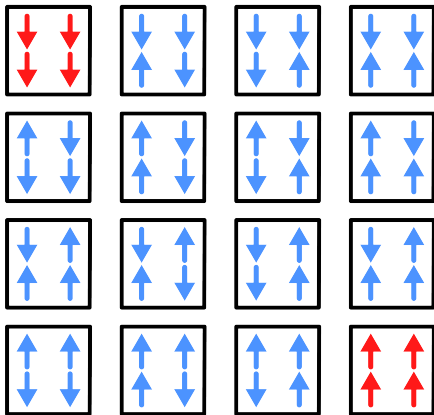


- pair energies $E_{ij} = +1$

2x2 Ising model

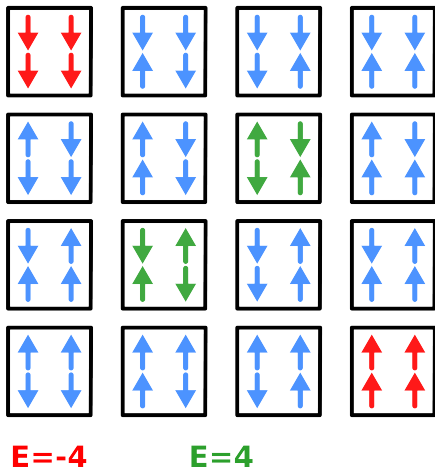


2x2 Ising model

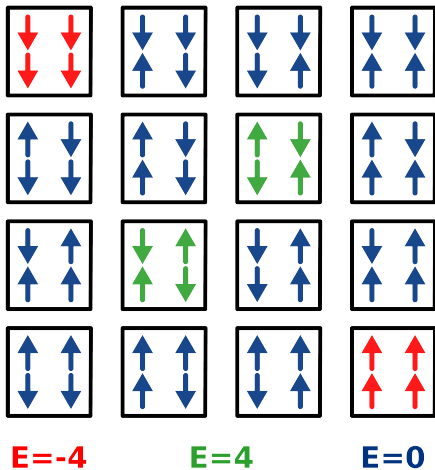


$$E = -4$$

2x2 Ising model



2x2 Ising model



Gray-code enumeration

$$[-1, -1, -1, -1] \quad E = -4$$

Gray-code enumeration

$$\begin{aligned} [-1, -1, -1, -1] & E = -4 \\ [1, -1, -1, -1] & E = 0 \end{aligned}$$

Gray-code enumeration

$[-1, -1, -1, -1]$	$E = -4$
$[1, -1, -1, -1]$	$E = 0$
$[1, 1, -1, -1]$	$E = 0$
$[-1, 1, -1, -1]$	$E = 0$

Gray-code enumeration

$[-1, -1, -1, -1]$	$E = -4$
$[1, -1, -1, -1]$	$E = 0$
$[1, 1, -1, -1]$	$E = 0$
$[-1, 1, -1, -1]$	$E = 0$
$[-1, 1, 1, -1]$	$E = 4$
$[1, 1, 1, -1]$	$E = 0$
$[1, -1, 1, -1]$	$E = 0$
$[-1, -1, 1, -1]$	$E = 0$



Gray-code enumeration

$[-1, -1, -1, -1]$	$E = -4$
$[1, -1, -1, -1]$	$E = 0$
$[1, 1, -1, -1]$	$E = 0$
$[-1, 1, -1, -1]$	$E = 0$
$[-1, 1, 1, -1]$	$E = 4$
$[1, 1, 1, -1]$	$E = 0$
$[1, -1, 1, -1]$	$E = 0$
$[-1, -1, 1, -1]$	$E = 0$
$[-1, -1, 1, 1]$	$E = 0$
$[1, -1, 1, 1]$	$E = 0$
$[1, 1, 1, 1]$	$E = -4$
$[-1, 1, 1, 1]$	$E = 0$



Gray-code enumeration

$[-1, -1, -1, -1]$	$E = -4$
$[1, -1, -1, -1]$	$E = 0$
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$[1, 1, 1, 1]$	$E = -4$
$[-1, 1, 1, 1]$	$E = 0$
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$[1, 1, -1, 1]$	$E = 0$
$[1, -1, -1, 1]$	$E = 4$
$[-1, -1, -1, 1]$	$E = 0$



```

def gray_flip(t, N):
    k = t[0]
    if k > N: return t, k
    t[k - 1] = t[k]
    t[k] = k + 1
    if k != 1: t[0] = 1
    return t, k

L = 4
N = L * L
nbr = {i : ((i // L) * L + (i + 1) % L, (i + L) % N,
           (i // L) * L + (i - 1) % L, (i - L) % N)
       for i in range(N)}

S = [-1] * N
E = -2 * N
print S, E
tau = range(1, N + 2)
for i in range(1, 2 ** N):
    tau, k = gray_flip(tau, N)
    h = sum(S[n] for n in nbr[k - 1])
    E += 2 * h * S[k - 1]
    S[k - 1] *= -1
print S, E

```



$$Z(\beta) = - \sum_{\substack{\sigma_0 = \pm 1 \\ \vdots \\ \sigma_{N-1} = \pm 1}} e^{-\beta E(\sigma_0, \dots, \sigma_{N-1})}$$



$$\begin{aligned} Z(\beta) &= - \sum_{\substack{\sigma_0 = \pm 1 \\ \vdots \\ \sigma_{N-1} = \pm 1}} e^{-\beta E(\sigma_0, \dots, \sigma_{N-1})} \\ &= \sum_E \mathcal{N}(E) e^{-\beta E} \end{aligned}$$

$$\langle E \rangle = \frac{\sum_{\sigma} E_{\sigma} e^{-\beta E_{\sigma}}}{\sum_{\sigma} e^{-\beta E_{\sigma}}}$$

$$\begin{aligned}\langle E \rangle &= \frac{\sum_{\sigma} E_{\sigma} e^{-\beta E_{\sigma}}}{\sum_{\sigma} e^{-\beta E_{\sigma}}} \\ &= \sum_E E \mathcal{N}(E) e^{-\beta E}\end{aligned}$$

```

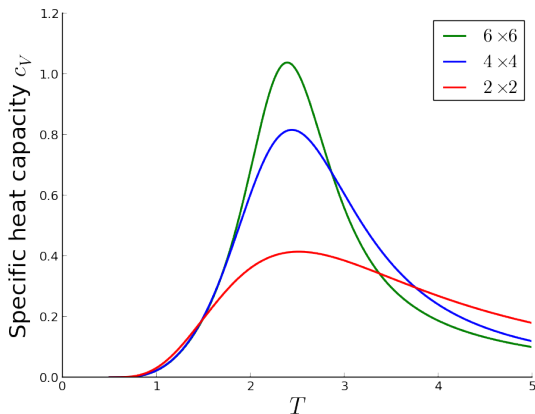
L = 4
N = L * L
nbr = {(i // L) * L + (i + 1) % L, (i + L) % N,
        (i // L) * L + (i - 1) % L, (i - L) % N} \
        for i in range(N)}

dos = {}
S = [-1] * N
E = energy(S, N, nbr)
dos[E] = 1
tau = range(1, N + 2)
for i in range(1, 2 ** N):
    tau, k = gray_flip(tau, N)
    E += 2 * sum(S[k - 1] * S[n] for n in nbr[k - 1])
    S[k - 1] *= -1
    if E in dos: dos[E] += 1
    else:        dos[E] = 1
for T in [0.1 * i for i in range(1, 51)]:
    Z = 0.0
    E_av = 0.0
    M_av = 0.0
    E2_av = 0.0
    for E in dos.keys():
        weight = math.exp(- E / T) * dos[E]
        Z += weight
        E_av += weight * E
        E2_av += weight * E ** 2
    E2_av /= Z
    E_av /= Z
    cv = (E2_av - E_av ** 2) / N / T

```

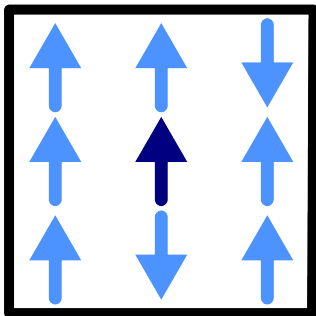


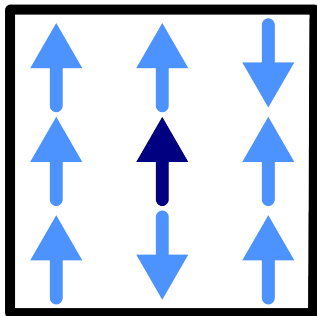
Specific heat of Ising model on finite lattices



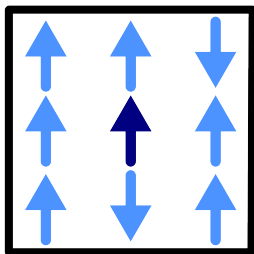
$$T_c = \frac{2}{\log(1 + \sqrt{2})} = 2.269\dots$$

Markov-chain sampling

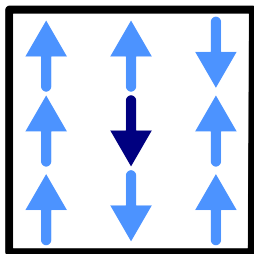




a



a



b

$$p^{\text{acc}}(a \rightarrow b) = \min \left(1, e^{-\beta(E_b - E_a)} \right)$$

```

import random, math

L = 16
N = L * L
nbr = {i : ((i // L) * L + (i + 1) % L, (i + L) % N,
           (i // L) * L + (i - 1) % L, (i - L) % N) \
       for i in range(N)}

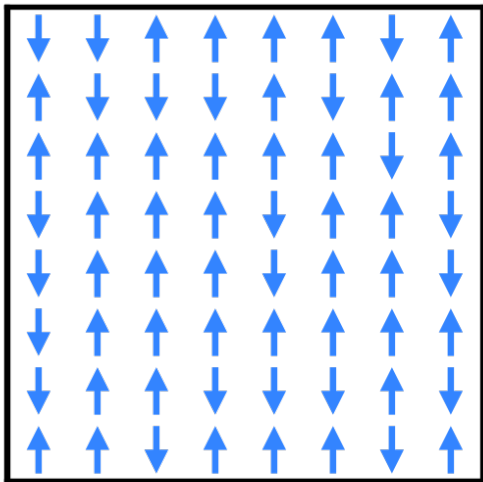
nsteps = 1000000
T = 2.0
beta = 1.0 / T
S = [random.choice([1, -1]) for k in range(N)]
for step in range(nsteps):
    k = random.randint(0, N - 1)
    delta_E = 2.0 * S[k] * sum(S[nn] for nn in nbr[k])
    if random.uniform(0.0, 1.0) < math.exp(-beta * delta_E):
        S[k] *= -1
print S, sum(S)

```

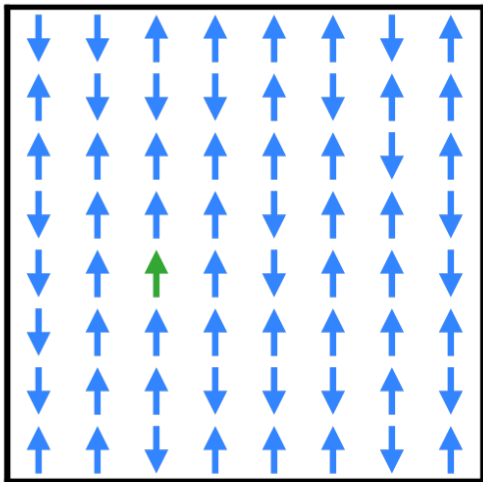


Configurations around T_c

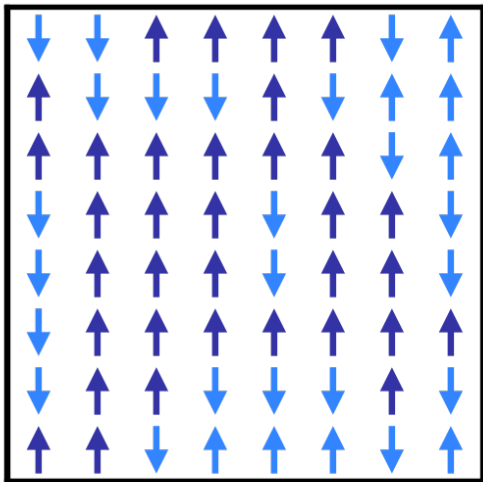
Cluster algorithm, first idea



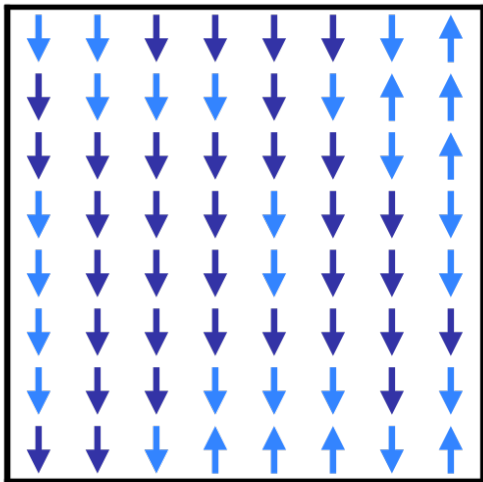
Cluster algorithm, first idea



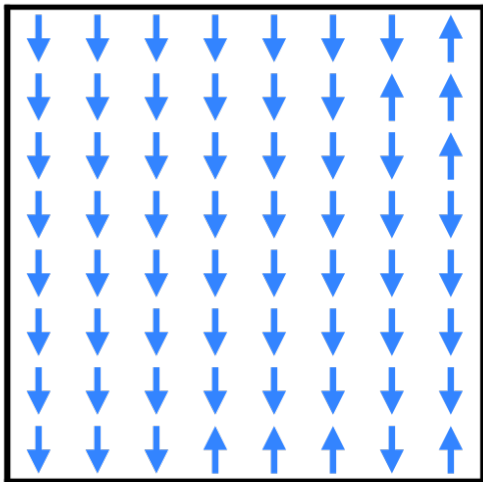
Cluster algorithm, first idea



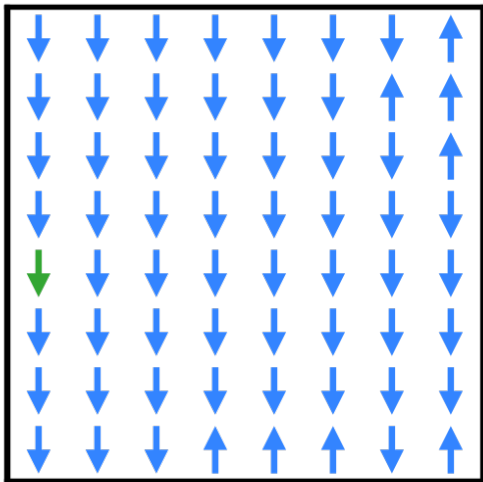
Cluster algorithm, first idea



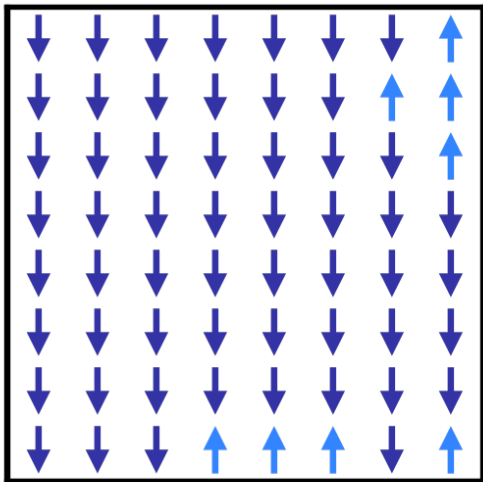
Cluster algorithm, first idea



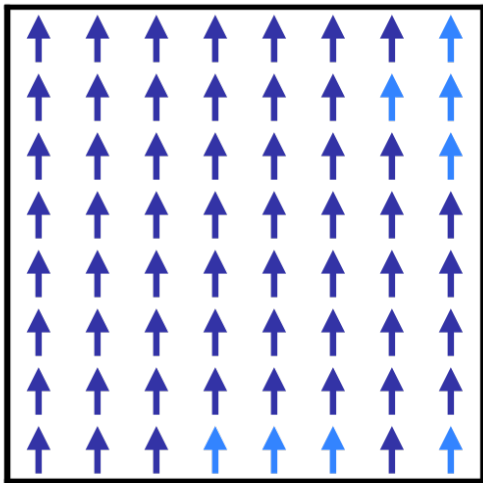
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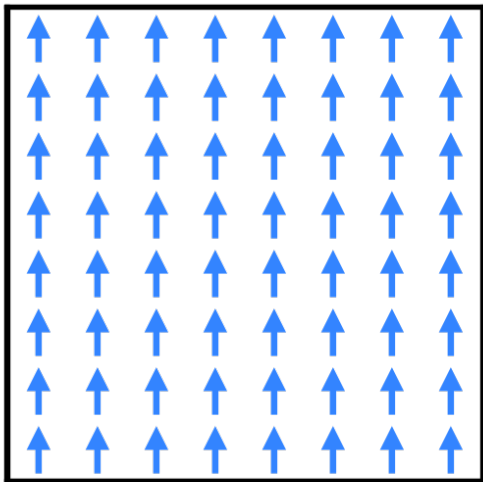
Cluster algorithm, first idea



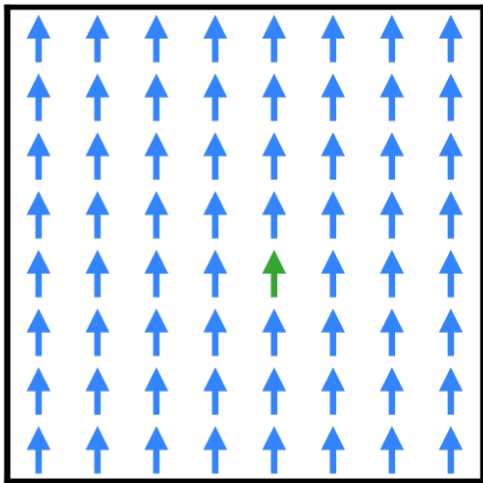
Cluster algorithm, first idea



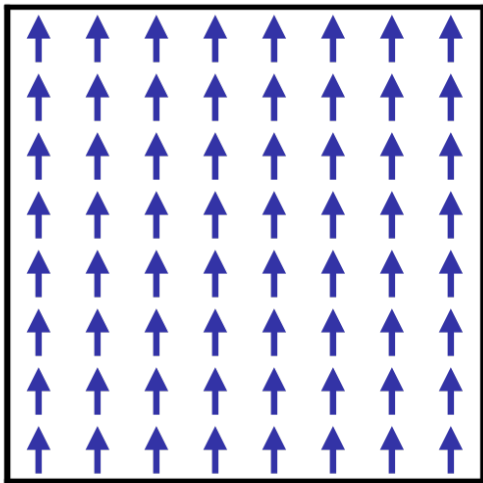
Cluster algorithm, first idea



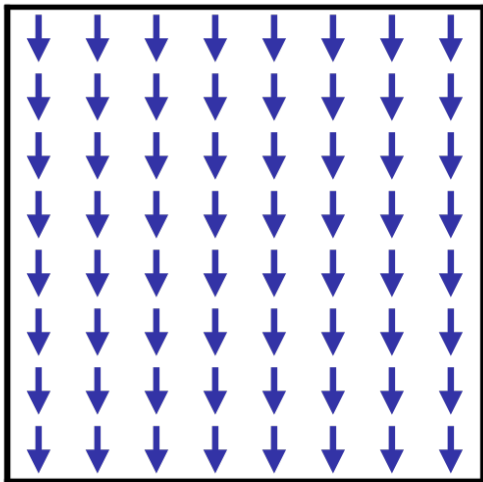
Cluster algorithm, first idea



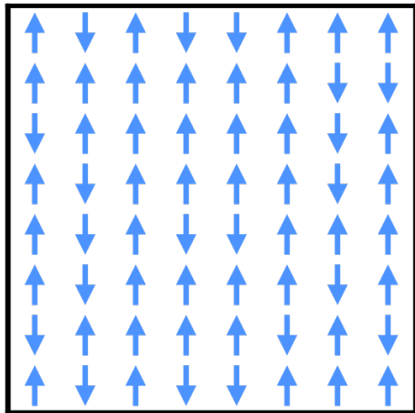
Cluster algorithm, first idea



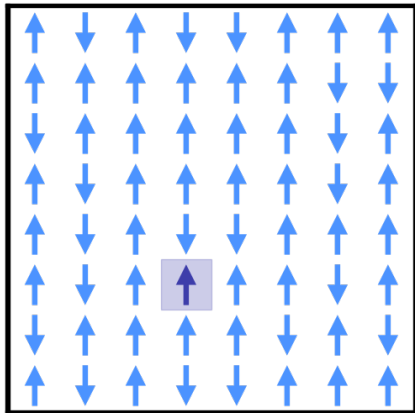
Cluster algorithm, first idea



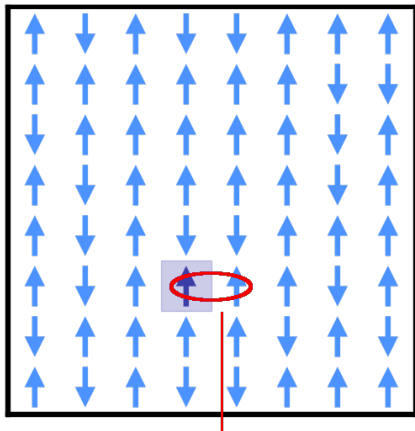
Cluster algorithm, probabilistic (Wolff, 1989)



Cluster algorithm, probabilistic (Wolff, 1989)

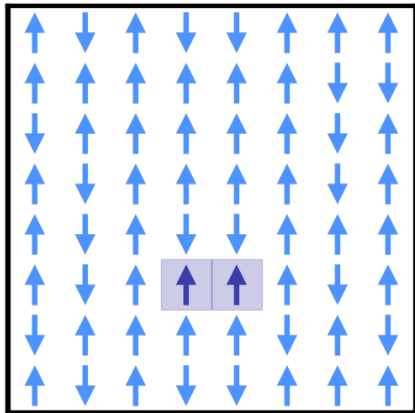


Cluster algorithm, probabilistic (Wolff, 1989)

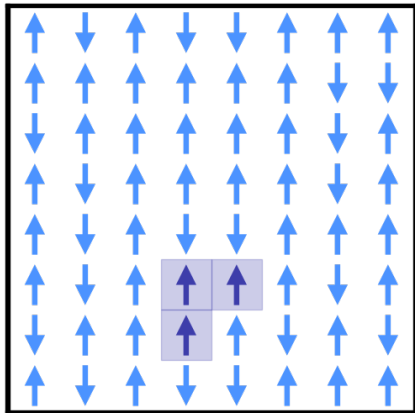


Add with probability p

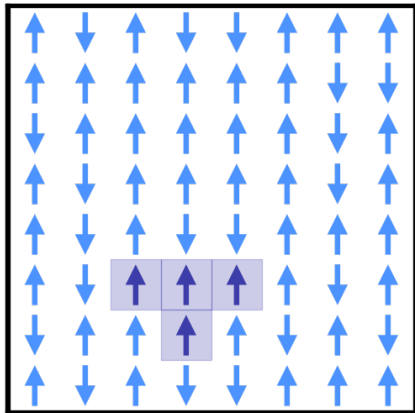
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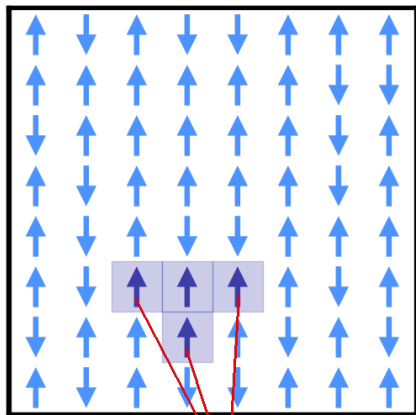
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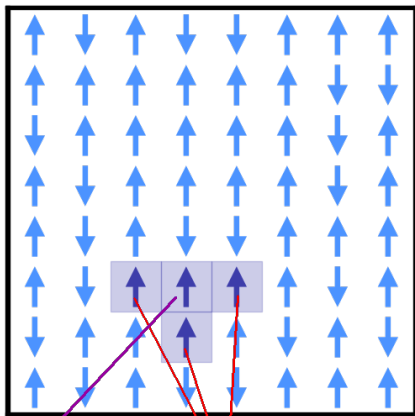


Cluster algorithm, probabilistic (Wolff, 1989)



New spins in cluster

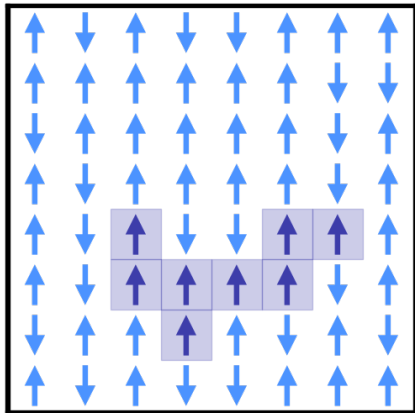
Cluster algorithm, probabilistic (Wolff, 1989)



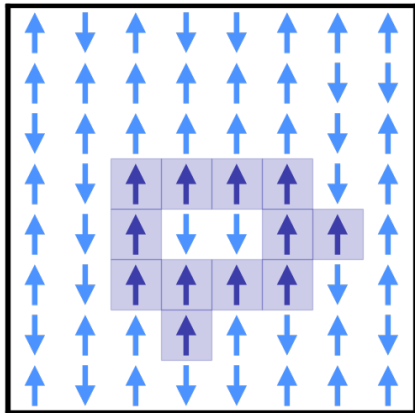
Spin already
present

New spins in cluster

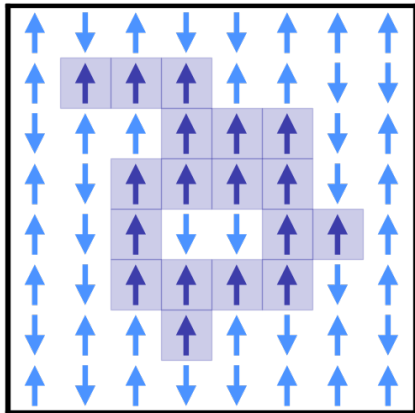
Cluster algorithm, probabilistic (Wolff, 1989)



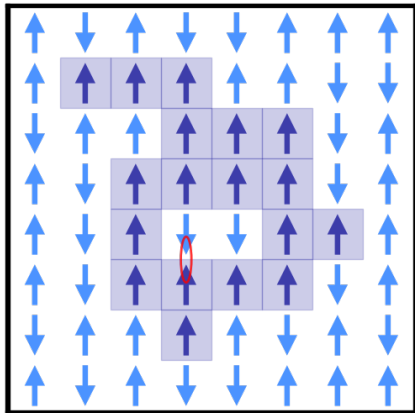
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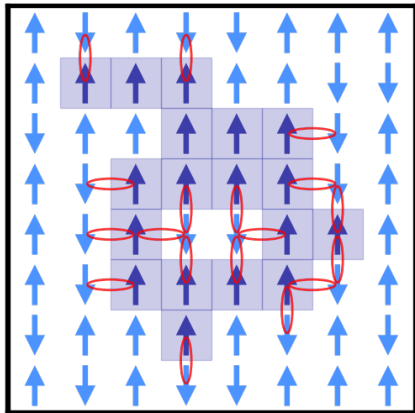
Cluster algorithm, probabilistic (Wolff, 1989)



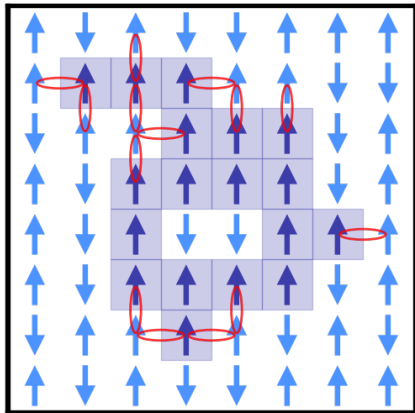
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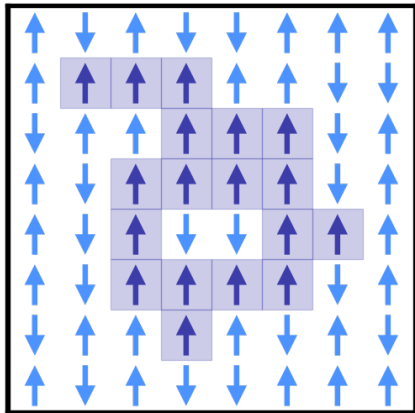
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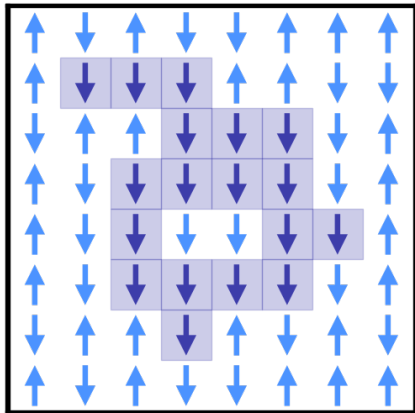
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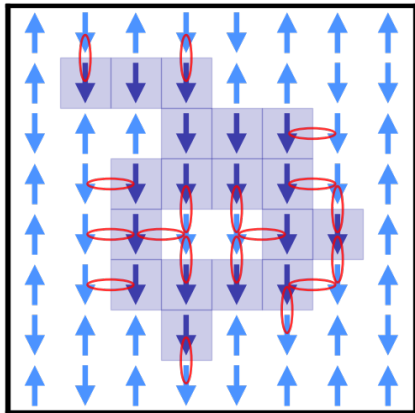
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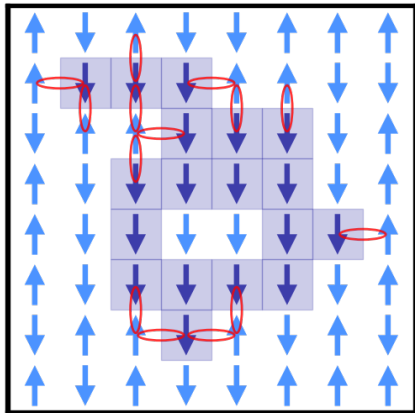
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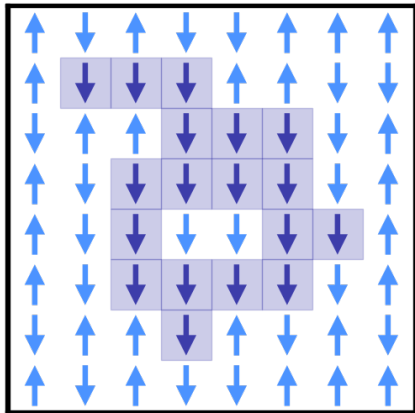
Cluster algorithm, probabilistic (Wolff, 1989)



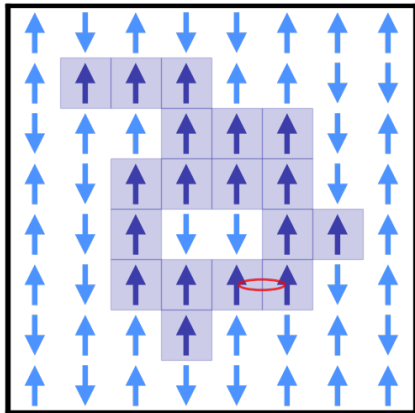
Cluster algorithm, probabilistic (Wolff, 1989)



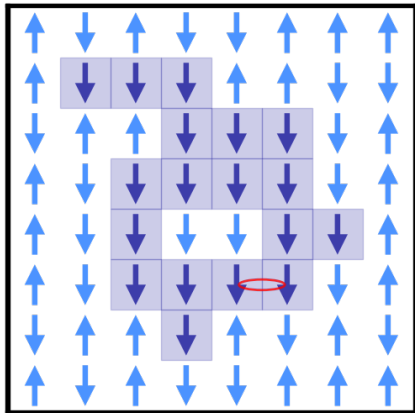
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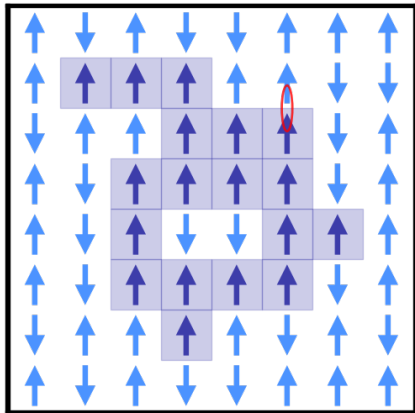
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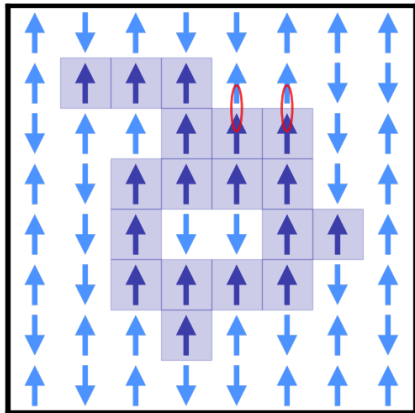
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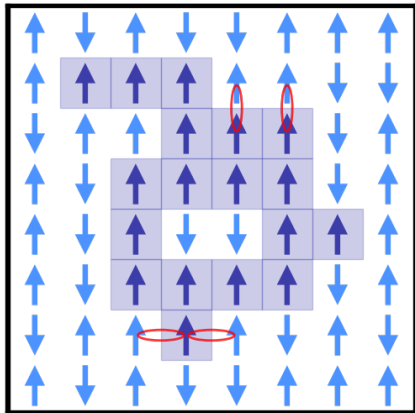
Cluster algorithm, probabilistic (Wolff, 1989)



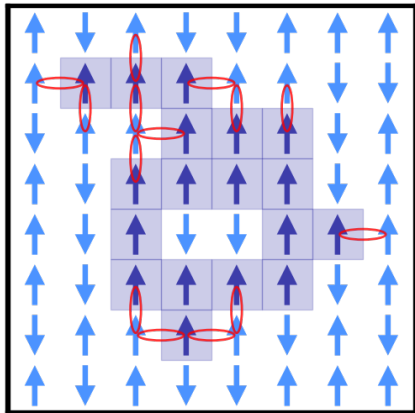
Cluster algorithm, probabilistic (Wolff, 1989)



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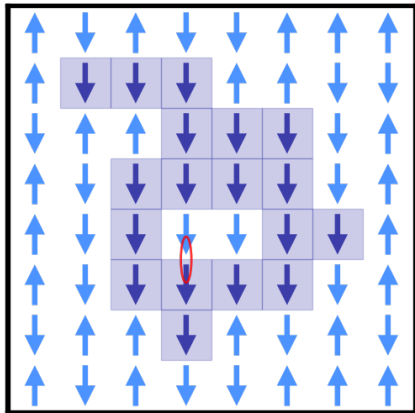


Cluster algorithm, probabilistic (Wolff, 1989)

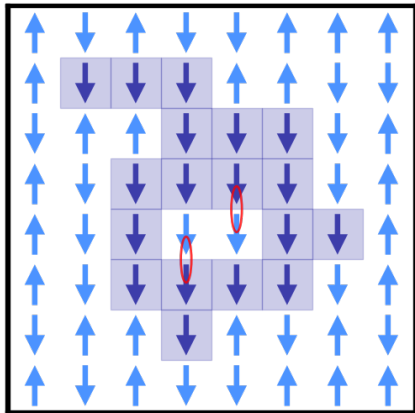


$$\mathcal{A}(a \rightarrow b) \propto (1 - p)^{14}$$

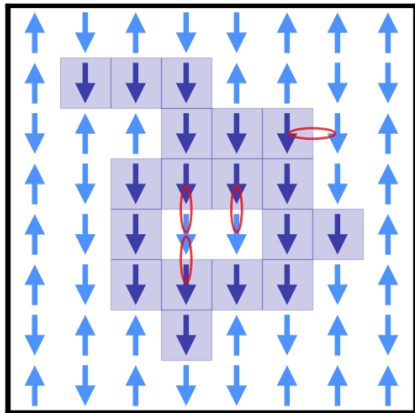
Cluster algorithm, probabilistic (Wolff, 1989)



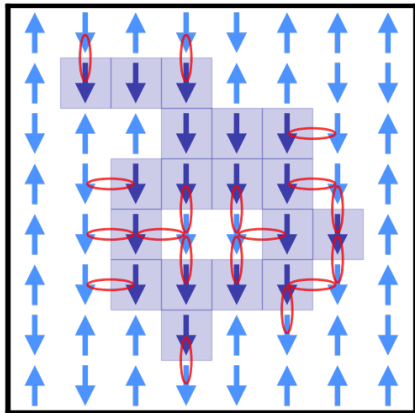
Cluster algorithm, probabilistic (Wolff, 1989)



Cluster algorithm, probabilistic (Wolff, 1989)

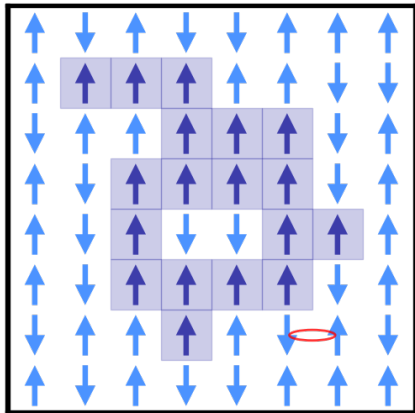


Cluster algorithm, probabilistic (Wolff, 1989)

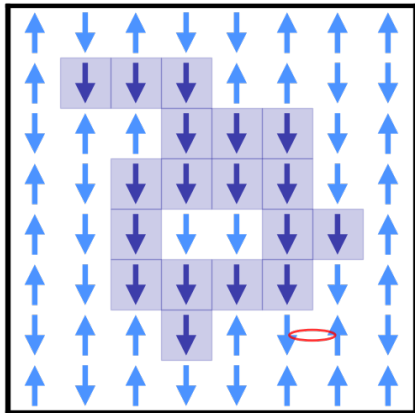


$$\mathcal{A}(b \rightarrow a) \propto (1 - p)^{18}$$

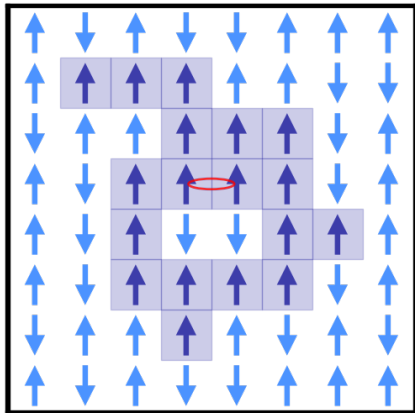
Cluster algorithm, probabilistic (Wolff, 1989)



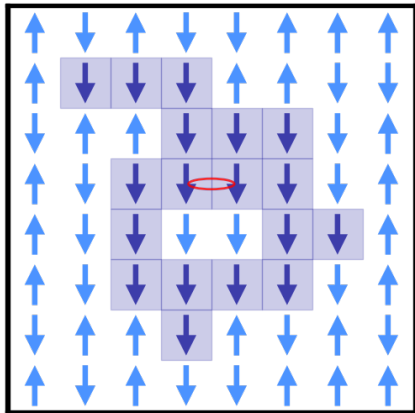
Cluster algorithm, probabilistic (Wolff, 1989)



Cluster algorithm, probabilistic (Wolff, 1989)



Cluster algorithm, probabilistic (Wolff, 1989)



energy of the boundary

=

$$n_1 - n_2$$

energy of the boundary

=

$$n_2 - n_1$$



$$n_1 = 18, \quad n_2 = 14$$

Detailed balance (Metropolis-Hastings)

$$e^{-\beta(n_1-n_2)}(1-p)^{n_2}p^{\text{acc}}(a \rightarrow b) = e^{-\beta(n_2-n_1)}(1-p)^{n_1}p^{\text{acc}}(b \rightarrow a)$$



Detailed balance (Metropolis-Hastings)

$$e^{-\beta(n_1-n_2)}(1-p)^{n_2}p^{\text{acc}}(a \rightarrow b) = e^{-\beta(n_2-n_1)}(1-p)^{n_1}p^{\text{acc}}(b \rightarrow a)$$

└─ $\pi(a)$ (depends on energy across boundaries)



Detailed balance (Metropolis-Hastings)

$$e^{-\beta(n_1 - n_2)} (1 - p)^{n_2} p^{\text{acc}}(a \rightarrow b) = e^{-\beta(n_2 - n_1)} (1 - p)^{n_1} p^{\text{acc}}(b \rightarrow a)$$

$\mathcal{A}(a \rightarrow b)$ (probability to stop construction)

$\pi(a)$ (depends on energy across boundaries)

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$$= 1$$

$$1 - p = e^{-2\beta} \quad \text{magic value}$$

```
import random, math
```

```
L = 100
```

```
N = L * L
```

```
nbr = {i : ((i // L) * L + (i + 1) % L, (i + L) % N,  
           (i // L) * L + (i - 1) % L, (i - L) % N)  
       for i in range(N)}
```

```
T = 2.5
```

```
p = 1.0 - math.exp(-2.0 / T)
```

```
nsteps = 10000
```

```
S = [random.choice([1, -1]) for k in range(N)]
```

```
for step in range(nsteps):
```

```
    k = random.randint(0, N - 1)
```

```
    Pocket, Cluster = [k], [k]
```

```
    while Pocket != []:
```

```
        j = random.choice(Pocket)
```

```
        for l in nbr[j]:
```

```
            if S[l] == S[j] and l not in Cluster \  
                and random.uniform(0.0, 1.0) < p:
```

```
                Pocket.append(l)
```

```
                Cluster.append(l)
```

```
    Pocket.remove(j)
```

```
for j in Cluster:
```

```
    S[j] *= -1
```



Running cluster-ising.py

Metropolis algorithm (reminder)

$$\pi(a) \mathcal{A}(a \rightarrow b) p^{\text{acc}}(a \rightarrow b) = \pi(b) \mathcal{A}(b \rightarrow a) p^{\text{acc}}(b \rightarrow a)$$

$$\mathcal{A}(a \rightarrow b) = \mathcal{A}(b \rightarrow a)$$



Metropolis algorithm (reminder)

$$\pi(a) \cancel{\mathcal{A}(a \rightarrow b)} p^{\text{acc}}(a \rightarrow b) = \pi(b) \cancel{\mathcal{A}(b \rightarrow a)} p^{\text{acc}}(b \rightarrow a)$$

$$\mathcal{A}(a \rightarrow b) = \mathcal{A}(b \rightarrow a)$$

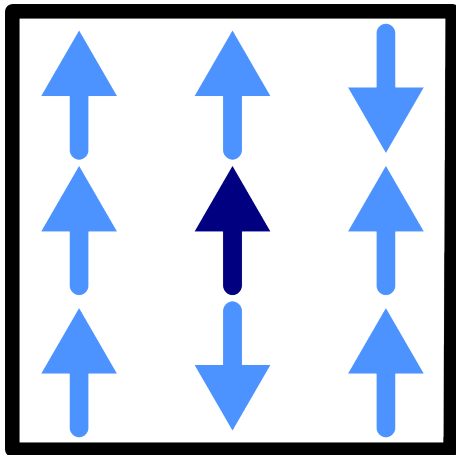


$$\pi(a) \mathcal{A}(a \rightarrow b) p^{\text{acc}}(a \rightarrow b) = \pi(b) \mathcal{A}(b \rightarrow a) p^{\text{acc}}(b \rightarrow a)$$

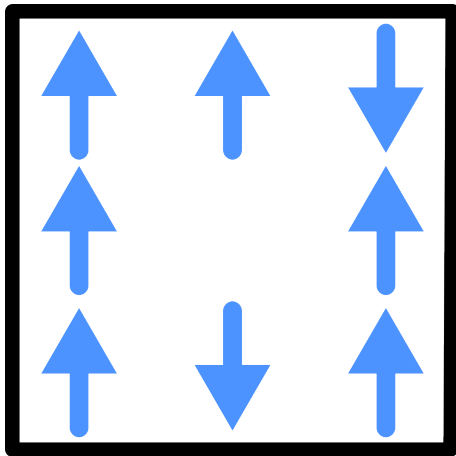
$$\mathcal{A}(a \rightarrow b) \propto \pi(b); \quad \mathcal{A}(b \rightarrow a) \propto \pi(a)$$

- Acceptance probabilities = 1
- Apply to subsystem

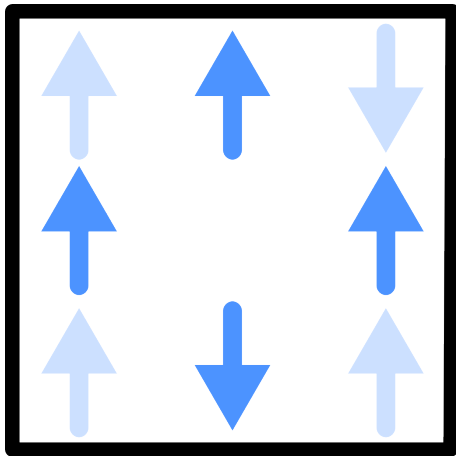
Heatbath algorithm



Heatbath algorithm



Heatbath algorithm



$$\pi^+ = \frac{e^{\beta h}}{e^{-\beta h} + e^{\beta h}}$$

$$\pi^- = \frac{e^{-\beta h}}{e^{-\beta h} + e^{\beta h}}$$




```
import random, math

L = 16
N = L * L
nbr = {i : ((i // L) * L + (i + 1) % L, (i + L) % N,
           (i // L) * L + (i - 1) % L, (i - L) % N) \
       for i in range(N)}

nsteps = 100000
beta = 0.5
S = [random.choice([1, -1]) for i in range(N)]
random.seed('123456')
for step in range(nsteps):
    k = random.randrange(N)
    Upsilon = random.uniform(0.0, 1.0)
    h = sum(S[nn] for nn in nbr[k])
    S[k] = -1
    if Upsilon < 1.0 / (1.0 + math.exp(-2.0 * beta * h)):
        S[k] = 1
```



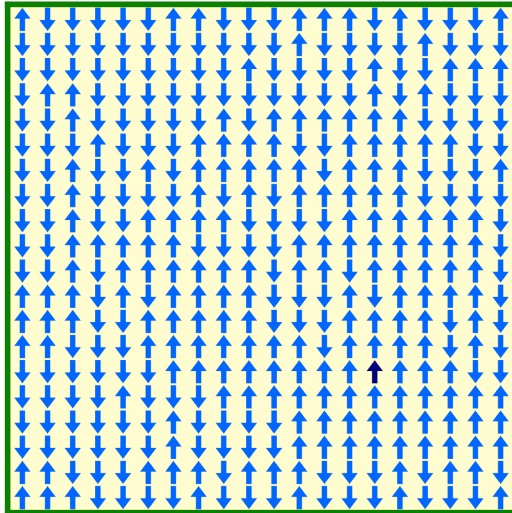
Running heatbath-ising.py from all up



Running heatbath-ising.py from all down

final configuration "up"

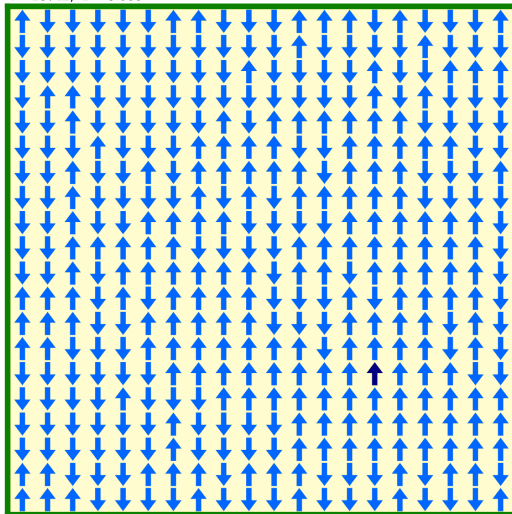
$t = 10742, \Upsilon = 0.588$



- Propp & Wilson 1996

final configuration "down"

$t = 10742$, $\Upsilon = 0.588$



- Propp & Wilson 1996

Coupling in heatbath-ising.py

```
import random, math

L = 16
N = L * L
nbr = {i : ((i // L) * L + (i + 1) % L, (i + L) % N,
           (i // L) * L + (i - 1) % L, (i - L) % N) \
       for i in range(N)}

nsteps = 100000
beta = 0.5
S = [random.choice([1, -1]) for i in range(N)]
random.seed('123456')
for step in range(nsteps):
    k = random.randrange(N)
    Upsilon = random.uniform(0.0, 1.0)
    h = sum(S[nn] for nn in nbr[k])
    S[k] = -1
    if Upsilon < 1.0 / (1.0 + math.exp(-2.0 * beta * h)):
        S[k] = 1
```



Concepts considered:

- Enumeration (Counting / Listing)
- Metropolis Markov-chain sampling
- Cluster algorithm & a priori probabilities
- Heat-bath algorithm
- Coupling

Algorithms considered:

- enumerate-ising.py (using Gray code)
- thermo-ising.py (using density of states)
- markov-ising.py (Metropolis algorithm)
- cluster-ising.py (Wolff algorithm)
- heat-bath-ising.py (and coupling)

