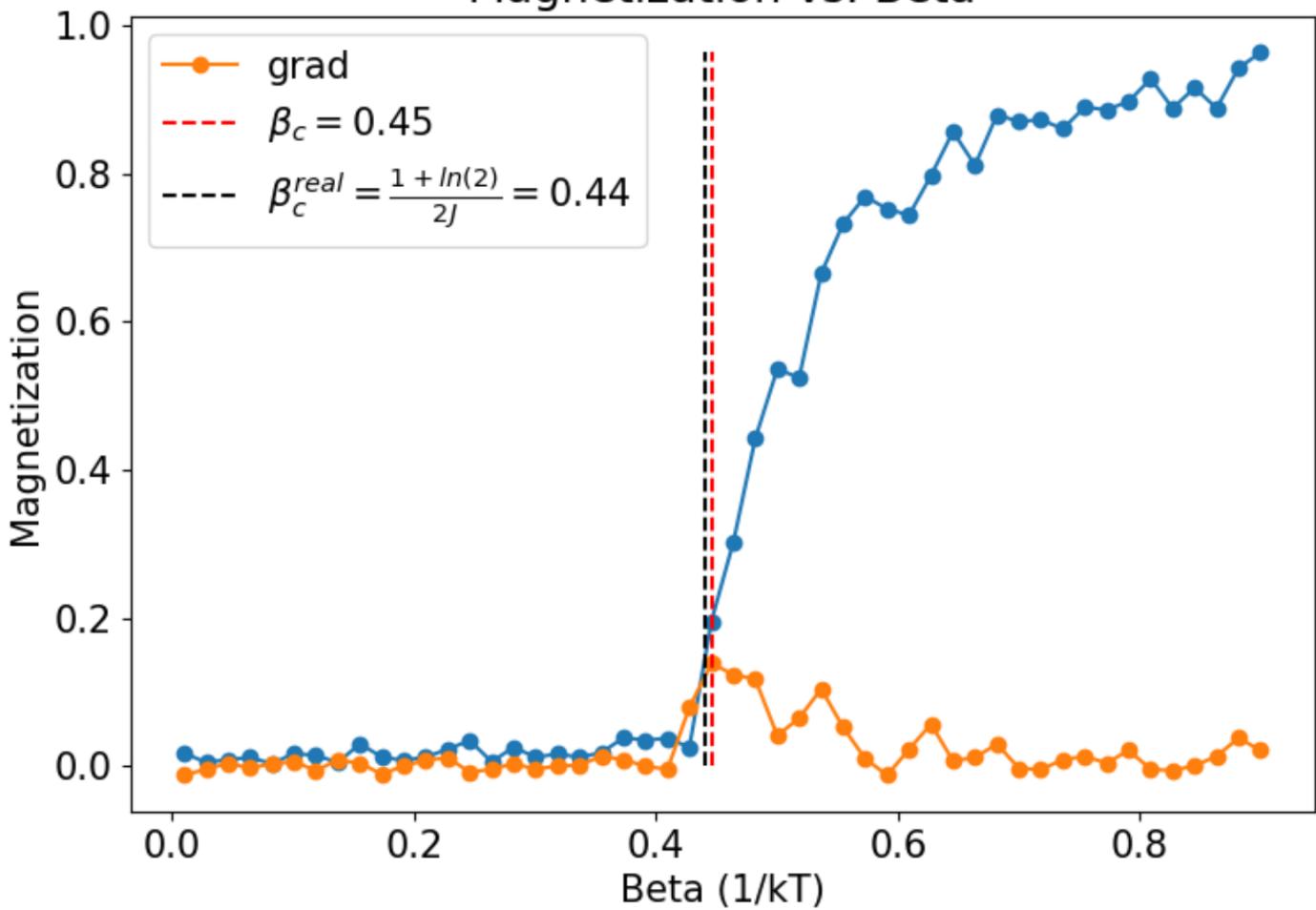


Magnetization vs. Beta



I found β_c by the maximum of the derivative

3) For anti-ferromagnet all that is required is

to adjust the check. We want to flip

spins around the random selected spin if

they're the opposite sign.

if $\text{spin-lattice}(i,j) == \text{cluster-spin}$ } anti-ferromagnet
 if $\text{spin-lattice}(i,j) == -\text{cluster-spin}$ ↓

and the prob. stays the same $P = 1 - e^{-\beta J}$

where $J \rightarrow -J$ for the system gains

energy when the spins are disaligned

Let's discuss the physics a bit. For an

anti-ferro magnet without external magnetic field there

will be no net magnetization for $T=0$, for

the two sub-lattices will cancel each other out.

For $T \rightarrow \infty$ there can be tiny magnetization

because the thermal fluctuations can produce

islands of magnetization, but it is insignificant.

With external magnetic field it is more interesting.

The interaction tries to disalign the spins but

the field tries to align them. At $B=0$

the thermal fluctuations will win and the field will

not be able to fight it.

As β increases the system starts to order. Without

the field, there will be no net mag. chg of J .

With the field theres an imbalance in the field direction, leading to non-zero mag. but a small one. As $\beta \rightarrow \infty$ theres strong ordering due to the field and J .

Again, no $h \rightarrow$ no M $h \rightarrow$ small M that saturates.

The point where M starts to rise, how fast it will rise, and at which value it will saturates, all depend on the ratio $\frac{\beta}{J}$.

4)

With magnetic field we have a small problem.

We can only calculate the energy diff $E_A - E_B$ after we construct the cluster, because it depends on the

size of the cluster. So we can construct the cluster as before and than add a check to see

if the cluster should flip based on the external field. The energy contribution is $e^{\alpha h_i S} = E_i$.

where α is the cluster spin direction and S is

the cluster size. and the probability will

be exactly this factor. Why not $1 - E_i$?

Lets check: for same orientation $E_i > 1$

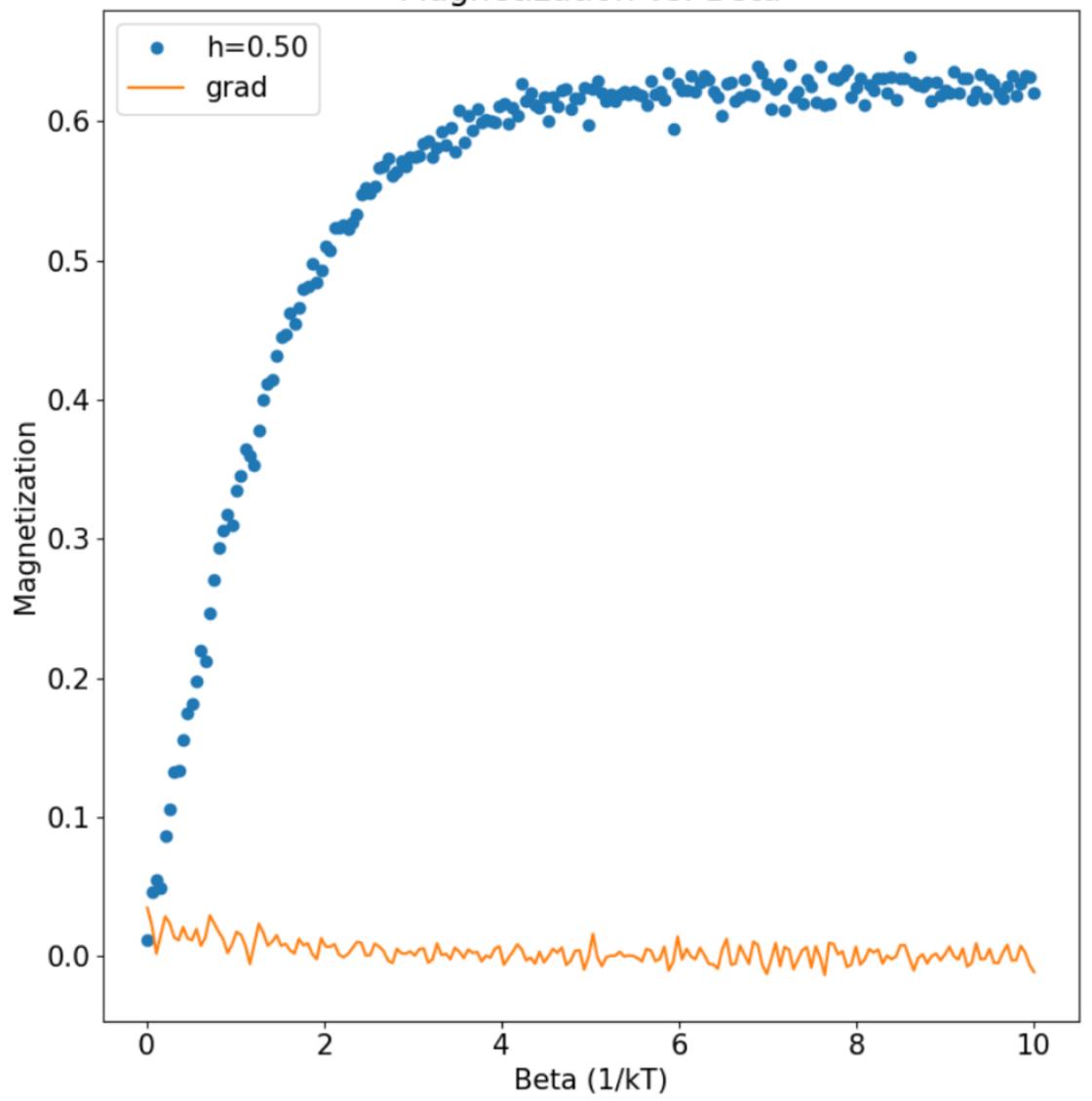
and the random number generator get numbers between

0 and 1, so it will always fail the check. (^{want} flip)

for opposite orientation $E_i < 1$ the check will only

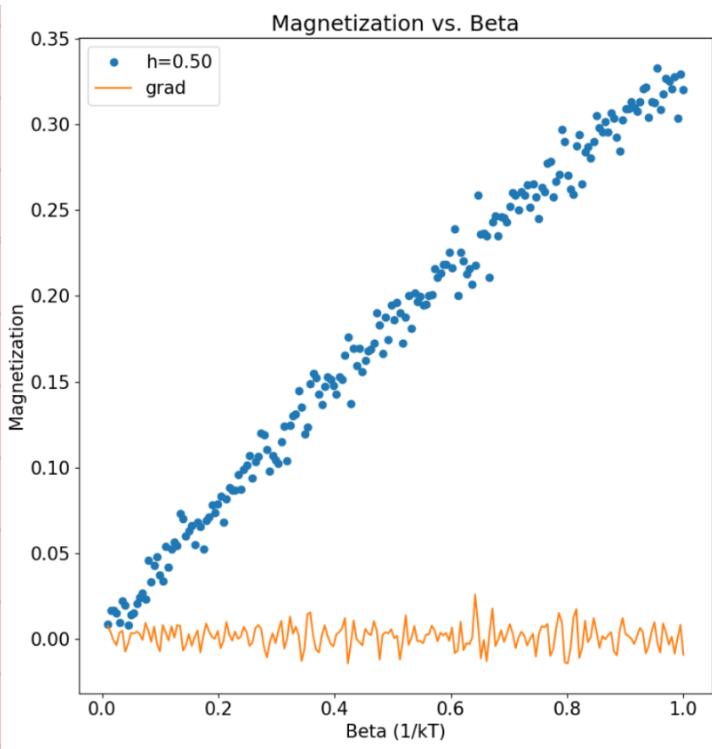
pass with regard to E_i which is basically the Boltzmann factor

Magnetization vs. Beta

 (h)

Anti-ferromagnet
with external mag.
field

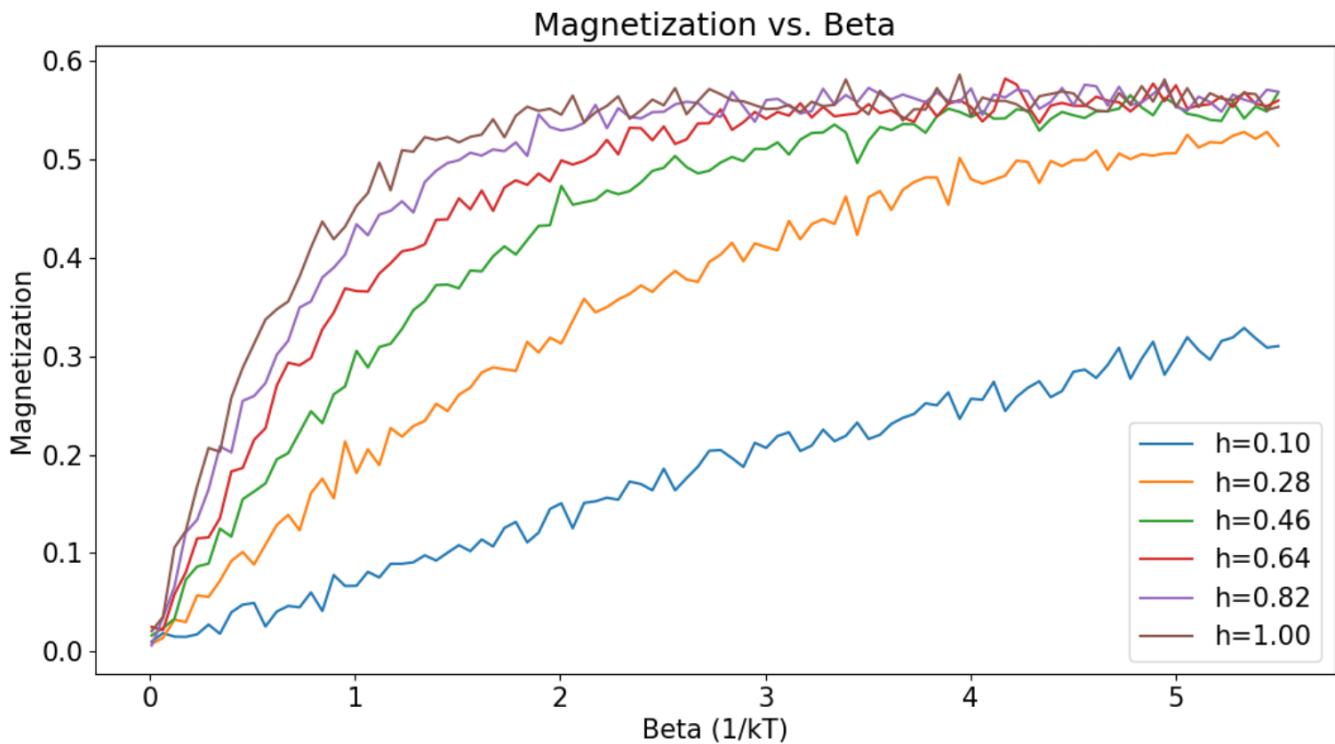
Unfortunately I can't seem to be
able to find β_c . Not numerically
and not by eye.



5) As h increases you need less thermal energy

to overcome J . h increases $\rightarrow T_c$ drops

h decreases $\rightarrow T_c$ increases



Although I can't see T_c at all, no matter h .

ex3_5.py

x

ex3q3__.py

x

ex3q3_6.png

x

```
def initialize_lattice(L):
    """Initialize the lattice with random spins (-1 or +1)."""
    return np.random.choice([-1, 1], size=(L, L))

def wolff_update(spin_lattice, beta, J, h):
    """Perform a single Wolff cluster update."""
    L = spin_lattice.shape[0]
    visited = np.zeros_like(spin_lattice, dtype=bool)

    # Pick a random seed spin
    x, y = np.random.randint(L), np.random.randint(L)
    cluster = [(x, y)]
    visited[x, y] = True
    cluster_spin = spin_lattice[x, y]

    # Define probability for adding a neighbor to the cluster
    add_prob = 1 - np.exp(-2 * beta * J)

    # Grow the cluster
    i = 0
    while i < len(cluster):
        cx, cy = cluster[i]
        neighbors = [
            ((cx - 1) % L, cy),
            ((cx + 1) % L, cy),
            (cx, (cy - 1) % L),
            (cx, (cy + 1) % L),
        ]

        for nx, ny in neighbors:
            if not visited[nx, ny] and spin_lattice[nx, ny] == np.sign(J)*cluster_spin:
                if np.random.rand() < add_prob:
                    cluster.append((nx, ny))
                    visited[nx, ny] = True
        i += 1

    # Flip the entire cluster
    if np.random.rand() < np.exp(2 * beta * h * len(cluster) * cluster_spin):
        for cx, cy in cluster:
            spin_lattice[cx, cy] *= -1

    return spin_lattice
```

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ex3_5.py ex3q3__.py ex3q3_6.png

```
return spin_lattice
```

```
def precompute_frames(L, beta, J, h, steps, method):
    """Precompute all frames for the simulation."""
    spin_lattice = initialize_lattice(L)
    highlight_cluster = np.zeros_like(spin_lattice, dtype=float)
    magnetizations = []
    frames = []

    for _ in range(steps):
        spin_lattice = wolff_update(spin_lattice, beta, J, h)
        frames.append((spin_lattice.copy(), highlight_cluster.copy()))
        magnetizations.append(np.abs(np.sum(spin_lattice)) / (L * L))
    return frames, magnetizations

def simulate(L, beta, J, steps, h=0, animate=True):
    """Simulate the Ising model on a 2D lattice."""
    frames, magnetizations = precompute_frames(L, beta, J, h, steps)

    if animate:
        fig, ax = plt.subplots()
        im = ax.imshow(frames[0][0], cmap="coolwarm", interpolation="nearest")
        cluster_overlay = ax.imshow(
            frames[0][1],
            cmap="Grays",
            alpha=0.2,
            interpolation="nearest",
            vmin=0,
            vmax=1,
        )

        def update(frame):
            nonlocal cluster_overlay, im
            spin_lattice, highlight_cluster = frames[frame]
            im.set_array(spin_lattice)
            cluster_overlay.set_array(highlight_cluster)
            return [im, cluster_overlay]

        ani = FuncAnimation(fig, update, frames=len(frames),
                            blit=True, repeat=False)
        plt.title("Spin Lattice Evolution")
        plt.colorbar(cluster_overlay, label="Spin")
        plt.show()
    else:
        return frames[-1][0], magnetizations
```

```
def plot_magnetization_vs_beta(L, J, h, steps, betas, method="wolff", plt_tc=False):
    """Plot the magnetization as a function of beta."""
NORMAL ➤ ↵ main > ▲ 5 ➤ ex3_5.py
```

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```

    ex3_5.py      ex3q3__.py      ex3q3_6.png
    return frames[-1][0], magnetizations

W def plot_magnetization_vs_beta(L, J, h, steps, betas, method="wolff", plt_tc=False):
    """Plot the magnetization as a function of beta."""
    magnetizations = []

    for beta in tqdm(betas, desc=f"Calculating Magnetization ({method})"):
        _, mags = precompute_frames(L, beta, J, h, steps, method)
        magnetizations.append(np.mean(mags))

    plt.plot(betas, magnetizations, marker="o", ls="None", label=f"h={h:.2f}")
    plt.plot(betas, np.gradient(magnetizations), label="grad")
    if plt_tc:
        imax = np.gradient(magnetizations).argmax()
        betac = betas[imax]
        plt.vlines(
            x=betac,
            ymin=0,
            ymax=max(magnetizations),
            colors="r",
            ls="dashed",
            label=rf"\beta_c={betac:.2f}",
        )
        plt.vlines(
            x=np.log(1 + np.sqrt(2)) / (2 * np.abs(J)),
            ymin=0,
            ymax=max(magnetizations),
            colors="k",
            ls="dashed",
            label=r"\beta_c^{real}=\frac{1+\ln(2)}{2J}=$"
            + rf"${np.log(1+np.sqrt(2))/(2*np.abs(J)):.2f}$",
        )
    plt.title("Magnetization vs. Beta")
    plt.xlabel("Beta (1/kT)")
    plt.ylabel("Magnetization")
    plt.legend()

if __name__ == "__main__":
    # Parameters
    L = 64 # Lattice size
    J = -1 # Interaction strength
    h = 0.5
    steps = 10000 # Number of Monte Carlo steps

    # Simulate with animation
    beta = 0.3
    # simulate(L, beta, J, steps, method="wolff", animate=True)

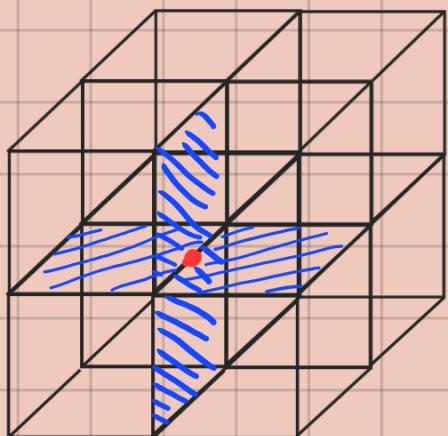
    # Plot magnetization vs beta for Wolff and Metropolis
    betas = np.linspace(0.01, 10, 200)
    hs = np.linspace(0.1, 1, 6)
    #for h in hs:
    plot_magnetization_vs_beta(L, J, h, steps, betas, plt_tc=0)
    plt.show()
    # betas = np.linspace(0.1, 10, 50)
    W # plot_magnetization_vs_beta(L, -J, 1000, betas, method="metropolis", h=0.5)

```

NORMAL ➤ ↵ main ➤ ▲ 5 ➤ ex3_5.py

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$$\textcircled{2} \quad H = -J \sum \sigma_1 \sigma_2 \sigma_3 \sigma_4$$

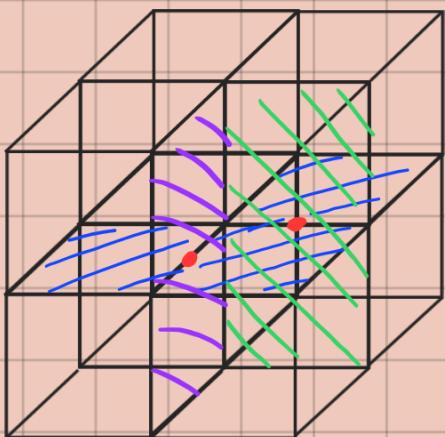
1st excitation:

4 plaquettes $\rightarrow t^4$

degeneracy: N sites \Rightarrow $6N$ edges

But each edge is shared between 2 sites, so we divide by 2 to avoid double counting

$$\Rightarrow \frac{6n}{2} = 3\overline{\underline{n}}$$



and excitation: two edges on the same plaquette

+ plaquettes but the shared plaquette
doesn't change sign $\rightarrow L^{7-2} = L^6$

degeneracy: $3N$ edges, next, there are 12 edges to pick from, but we don't care which is which so we divide by σ : $\frac{3N \cdot 12}{\sigma} = 18N$

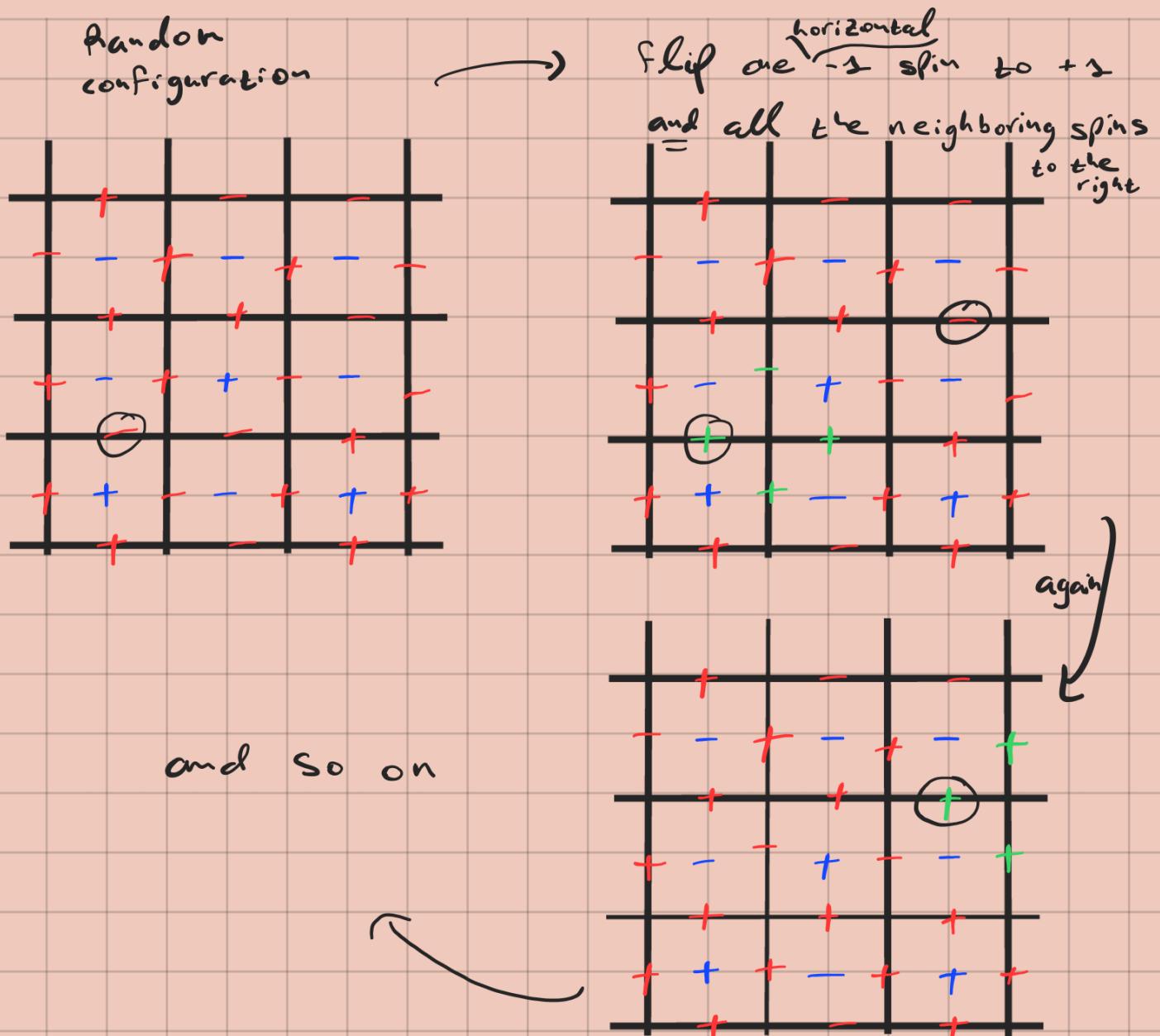
overall: $2^N e^{Nt^6} (1 + 3Nt^6 + 18Nt^{12} + \dots)$ where N_p = number of plaquettes

And what we saw is class: $2^N \cosh^{3^N} (1 + 3NE + 18NE^2 + \dots)$

$$\Rightarrow \underset{\text{low temp}}{Z(N, k)} = \underset{\text{high temp}}{Z(N, \tilde{k})} e^{\frac{\hbar \omega}{k_B T} \cosh^{-2n}(\tilde{k})}$$

I_t is Dual.

2)



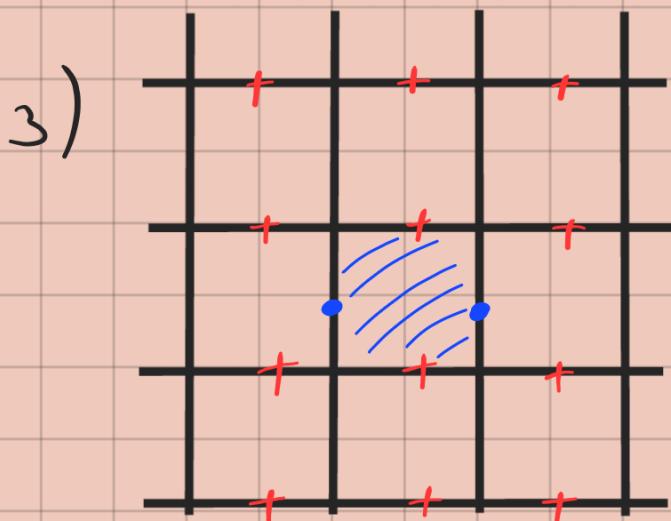
Why this works? because when you flip the 4 edges coming out of a vertex, the 4 plaquettes that might change value don't. Why? Because you flip 2 spins for each plaquette which doesn't change its value. And for the Horizontal = 1 you don't need to flip at all so its obviously doesn't change the value of the plaquette.

With this algorithm we got a gauge trans. such that every micro state is equivalent to a different micro state but with all $G_H = 1$:

- visit every G_H

- if $G_H = +1$

- flip G_H and 3 of its neighbors to the right



The contribution of each plaquette

is determined by 3 spins.

$$\begin{aligned} \text{so, } H &= -J \sum_P G_1^P G_2^P G_3^P G_4^P \\ &= -J \sum_P G_1^P G_3^P \end{aligned}$$

We get that each row of plaquettes is completely decoupled from its neighbours.

Let's assume M rows and N cols.

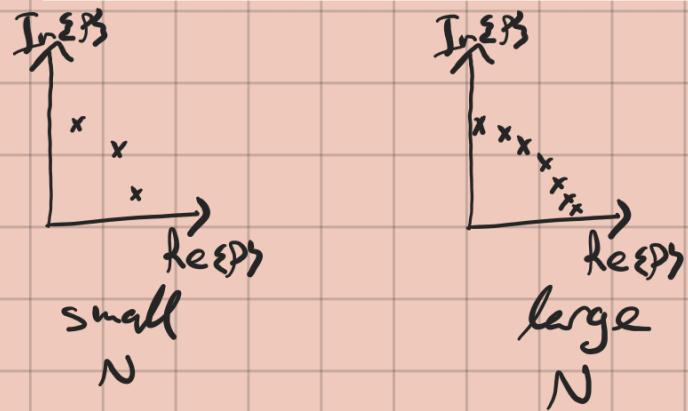
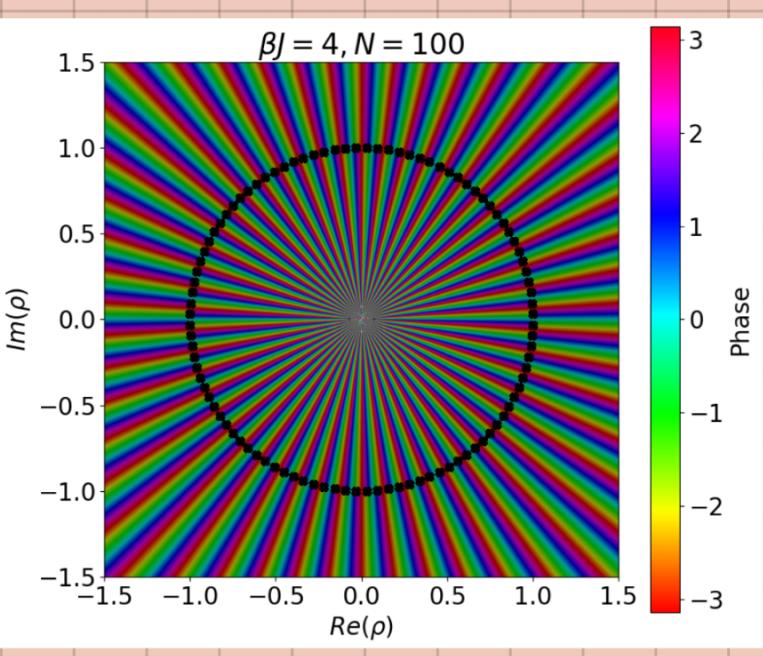
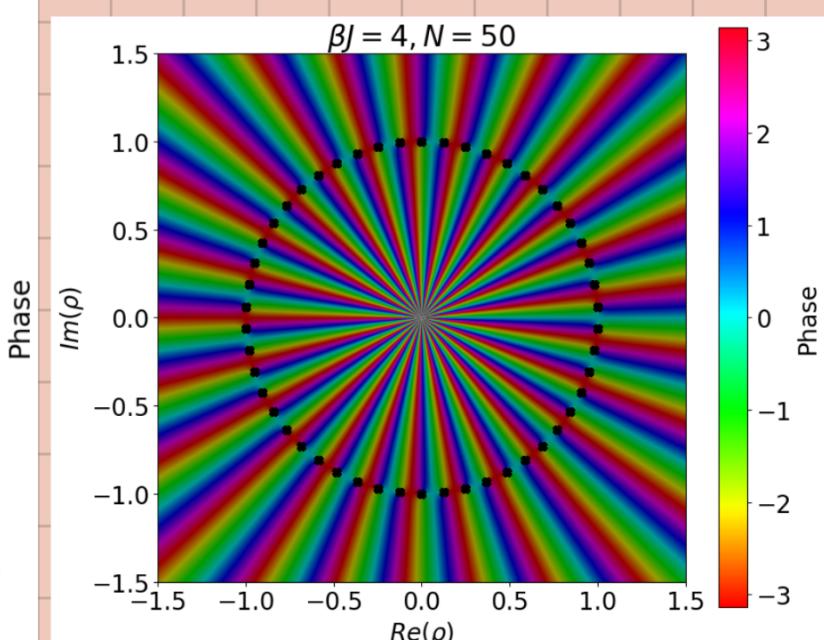
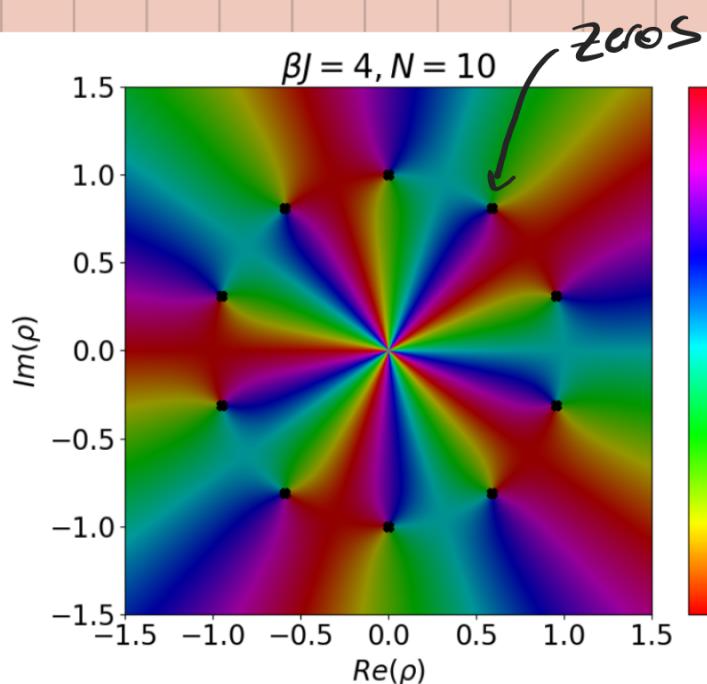
$$\begin{aligned} \Rightarrow Z &= \prod_i Z_i \quad ; \quad Z_i = \sum_{G_i} e^{B_j \sum_{ij} G_i G_j} = \lambda_+^N + \lambda_-^N = 2^N (\cosh^N \beta_j + \sinh^N \beta_j) \\ \left(\begin{array}{cc} e^{B_j} & e^{B_j} \\ e^{B_j} & e^{B_j} \end{array} \right) \rightarrow \lambda_{\pm} &= e^{B_j} \pm \bar{e}^{B_j} \quad \Rightarrow Z = 2^{N+M} (\cosh^N \beta_j + \sinh^N \beta_j)^M \end{aligned}$$

$$③ \lambda_{\pm} = e^{\beta J} \cosh \beta B \pm \sqrt{e^{2\beta J} \cosh^2 \beta B - 2 \sinh \beta B}$$

$$\rho = e^{-\beta B} \quad z = e^{-\beta J}$$

$$\sqrt{e^{\beta J} \cosh^2 \beta B} = \sqrt{e^{2\beta J} \cosh^2 \beta B - 2 \sinh \beta B}$$

$$\sqrt{\frac{1}{\rho} z (\rho + z + \frac{1}{\rho})} = \sqrt{\frac{1}{\rho} z (\rho + z + \frac{1}{\rho}) - (\frac{1}{z} - z)}$$



As N grows the zeroes come closer and closer to the real line. In the thermodynamic limit

$N \rightarrow \infty$ there will be two solutions on the real line $\rho = \pm 1$

And only then the system has two ground states and F is non-analytic in $B \rightarrow \infty$ ($T=0$)



$B=0$

```

    ex3_5.py      x | ex3q3__.py      x | ex3q3_6.png      x | ex3q3_.py      x
N = 14
bJ = 4
tau = np.exp(-2 * bJ)

def lambda_minus(rho):
W   # return 1 / (2 * np.sqrt(tau * rho)) * (1 + rho - np.sqrt(rho**2 + 2 * rho + tau**2))
a = (1/rho + 2 + rho) / (4*tau)
    return np.sqrt(a) - np.sqrt(a - 1/tau + tau)
W   #return (1 / np.sqrt(rho) + np.sqrt(rho))/(2*np.sqrt(tau)) - np.sqrt((1 / np.sqrt(rho) + np.sqrt(rho))**2 /
(4*tau) - tau - 1/tau)

def lambda_plus(rho):
W   # return 1 / (2 * np.sqrt(tau * rho)) * (1 + rho + np.sqrt(rho**2 + 2 * rho + tau**2))
a = (1 / rho + 2 + rho) / (4 * tau)
    return np.sqrt(a) + np.sqrt(a - 1 / tau + tau)
W   #return (1 / np.sqrt(rho) + np.sqrt(rho))/(2*np.sqrt(tau)) + np.sqrt((1 / np.sqrt(rho) + np.sqrt(rho))**2 /
(4*tau) - tau - 1/tau)

def part_f(z):
    return lambda_plus(z) ** N + lambda_minus(z) ** N

# Set up the range for the complex plane
x = np.linspace(-1.5, 1.5, 1000) # Real part range
y = np.linspace(-1.5, 1.5, 1000) # Imaginary part range
X, Y = np.meshgrid(x, y) # Create a grid
Z = X + 1j * Y # Combine to create complex numbers

# Compute the function values
z = part_f(Z)

# Compute magnitude and phase for visualization
magnitude = np.abs(z)
phase = np.angle(z)

# Normalize magnitude for color intensity
# Use log scale for better contrast
magnitude_normalized = np.log(1 + magnitude)

# Create a color representation
hsv = np.zeros(Z.shape + (3,))
hsv[:, :, 0] = (phase + np.pi) / (2 * np.pi) # Hue (normalized phase)
hsv[:, :, 1] = 1 # Saturation
hsv[:, :, 2] = magnitude_normalized / np.max(magnitude_normalized) # Value
■

# Convert HSV to RGB for plotting
rgb = hsv_to_rgb(hsv)

```

```

    ex3_5.py      ex3q3__.py      ex3q3_6.png      ex3q3_.py
rgb = hsv_to_rgb(hsv)

# Find zeros of the function
def real_imag_to_complex(v):
    """Helper function to convert real/imaginary input to complex output for root-finding."""
    return v[0] + 1j * v[1]

def complex_to_real_imag(c):
    """Helper function to convert complex input to real/imaginary for root-finding."""
    return [c.real, c.imag]

def objective(v):
    """Objective function for root-finding."""
    z = real_imag_to_complex(v)
    f_val = part_f(z)
    return [f_val.real, f_val.imag]

ix = np.linspace(-1.2, 1.2, 100)
iy = np.linspace(-1.2, 1.2, 100)
# Search for zeros in the grid
initial_guesses = []
for _x in ix:
    for _y in iy:
        initial_guesses.append([_x, _y])
zeros = []

for guess in initial_guesses:
    res = root(
        objective, guess, method="hybr", tol=1e-8
    ) # Use 'hybr' method for multidimensional root finding
    if res.success:
        zero = real_imag_to_complex(res.x)
        if zero not in zeros: # Avoid duplicates
            zeros.append(zero)

# Plot the result
fig, ax = plt.subplots(figsize=(8, 6))
img = ax.imshow(rgb, extent=[x.min(), x.max(),
                             y.min(), y.max()], origin="lower")
ax.set_xlabel(r"$\text{Re}(\rho)$")
ax.set_ylabel(r"$\text{Im}(\rho)$")
ax.set_title(rf"$\beta J = \{bJ\}, N = \{N\}$")

# Add a colorbar for the phase
norm = Normalize(vmin=-np.pi, vmax=np.pi)
sm = ScalarMappable(cmap="hsv", norm=norm)
sm.set_array([])
cbar = plt.colorbar(sm, ax=ax, orientation="vertical", label="Phase")

# Overlay zeros
zeros_real = [z.real for z in zeros]
zeros_imag = [z.imag for z in zeros]
ax.plot(zeros_real, zeros_imag, ms=7, marker="X", c="k", ls="None")
plt.show()

```

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