

1.

$$\begin{aligned}
p(y_i = 1 | y_{-i}, b, w) &= \frac{p(y_i = 1, y_{-i} | b, w)}{p(y_{-i} | b, w)} \\
&= \frac{p(y | b, w)}{p(y_{-i} | b, w)} \\
&= \frac{\frac{1}{Z} \prod_{l=1}^d \exp(b_l y_l) \prod_{(l,j) \in \text{pairs}} \exp(w_{lj} y_l y_j)}{\sum_{y_i = \pm 1} \frac{1}{Z} \prod_{l=1}^d \exp(b_l y_l) \prod_{(l,j) \in \text{pairs}} \exp(w_{lj} y_l y_j)}
\end{aligned}$$

since we are conditioning on  $y_{-i}$ . for the denominator we can sum over all possible assignments of  $y_i$ ,

We can simplify the numerator by removing the factors that do not depend on  $y_i$ :

$$p(y_i = 1 | y_{-i}, b, w) = \frac{\exp(b_i) \prod_{(j) \in \text{nb}(i)} \exp(w_{ij} y_j)}{\exp(b_i) \prod_{(j) \in \text{nb}(i)} \exp(w_{ij} y_j) + \exp(-b_i) \prod_{(j) \in \text{nb}(i)} \exp(-w_{ij} y_j)}$$

$$\text{Let } s' = b_i + \sum_{j \in \text{nb}(i)} w_{ij} y_j \text{ and } \exp(i+j) = \exp(i) \exp(j)$$

$$= \frac{\exp(s')}{\exp(s') + \exp(-s')} = \frac{1}{1 + \exp(-2s')}$$

$$1/(1 + \exp(-2s')) = \frac{1}{1 + \exp(-2(b_i + \sum_{j \in \text{nb}(i)} w_{ij} y_j))}$$

$$\text{lets say } -s = -2(b_i + \sum_{j \in \text{nb}(i)} w_{ij} y_j)$$

$$= \frac{1}{1 + \exp(-s)} = \sigma(s)$$

$$p(y_i = 1 | y_{-i}, b, w) = \sigma(s)$$

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**Algorithm 1** Gibbs sampling

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2. **Require:**  $iteration, b, w$

initialize : samples: empty list

initialize :  $y^0 \in \mathbb{R}^d$

**for**  $i$  from 1 to ( $iteration$ ) **do**

**for**  $j$  from 1 to  $d$  **do**

    pairs are  $1, \dots, d \times 1, \dots, d$  such that  $w_{ij}$  non zero

$nb_j = [k \text{ for } k \text{ in range}(d) \text{ if } (j,k) \text{ in pairs or } (k,j) \text{ in pairs}]$

$p_j = 1 / (1 + \exp(-2 * b[i] - 2 * \sum(w[i][k] * y[k] \text{ for } k \text{ in range}(nb_j))))$

**if**  $\text{random}() < p_j$  **then**

$y[j] = 1$

**else**

$y[j] = -1$

**end if**

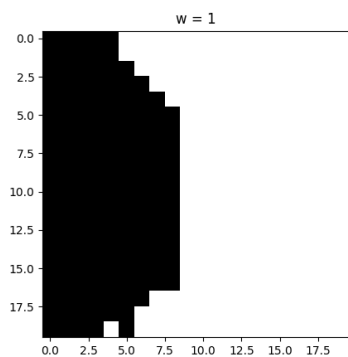
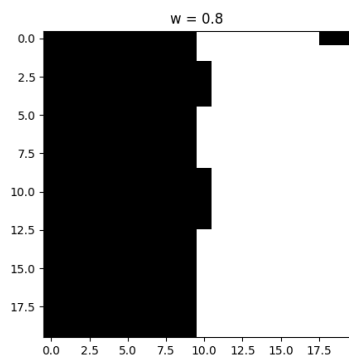
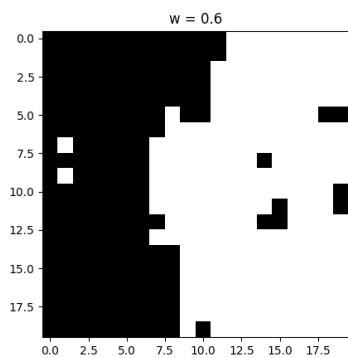
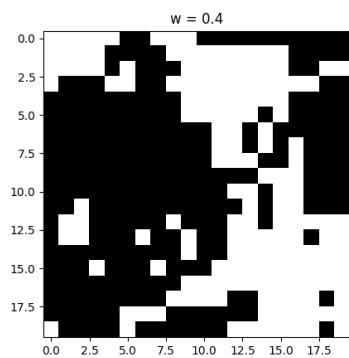
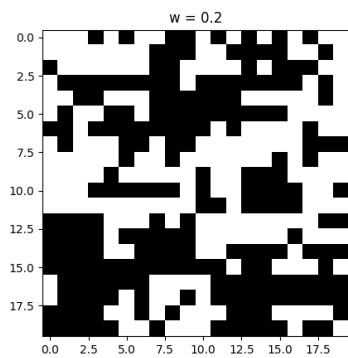
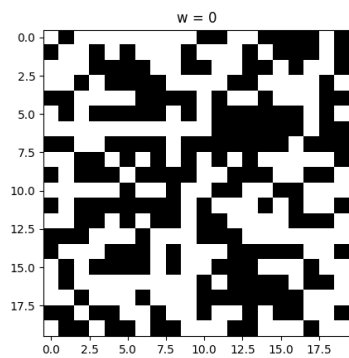
**end for**

  samples.append( $y$ .copy())

**end for**

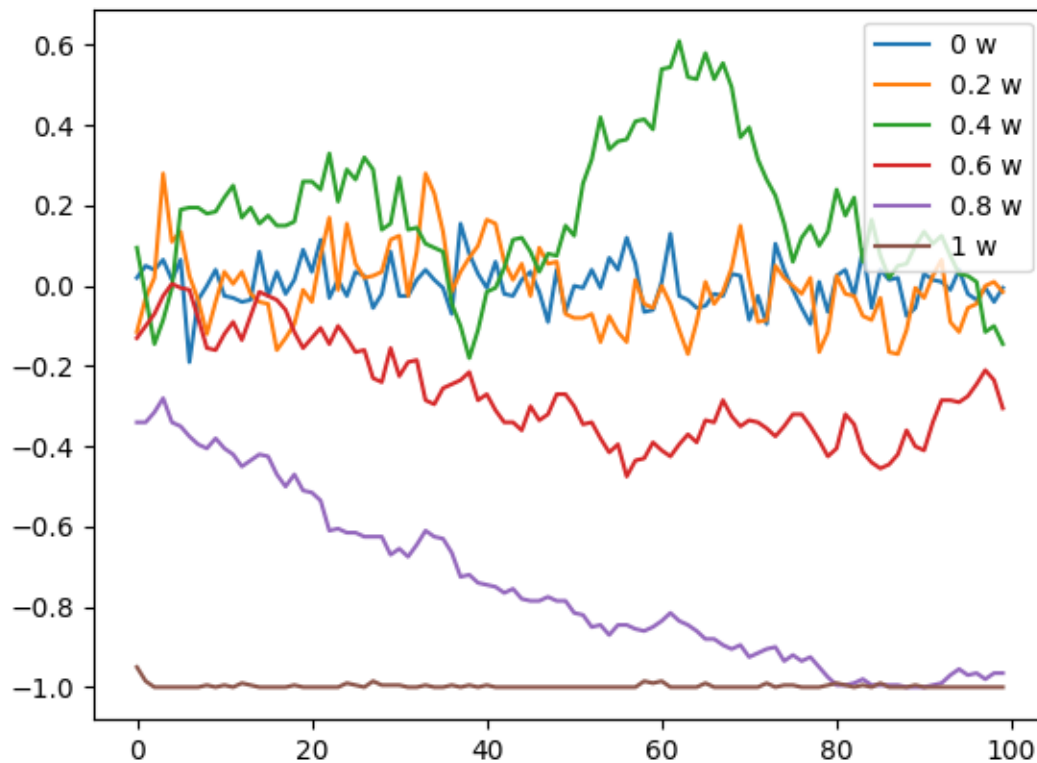
**return** samples

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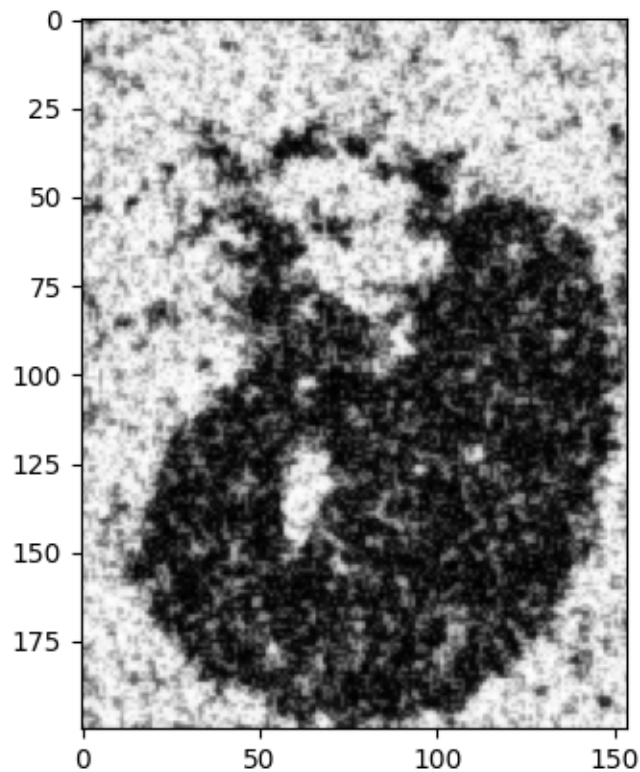
3.

4. since  $w_{ij}$  is increases, each pixel is trying to have same value with its neighbors, in other words, we can define clear regions between black(-1) and white(+1). This is because as  $w$  increases value of  $\sum_{j \in nb(i)} w_{ij} y_j$  matters more. Which represent value of neighbors affect more to decide  $y_i$



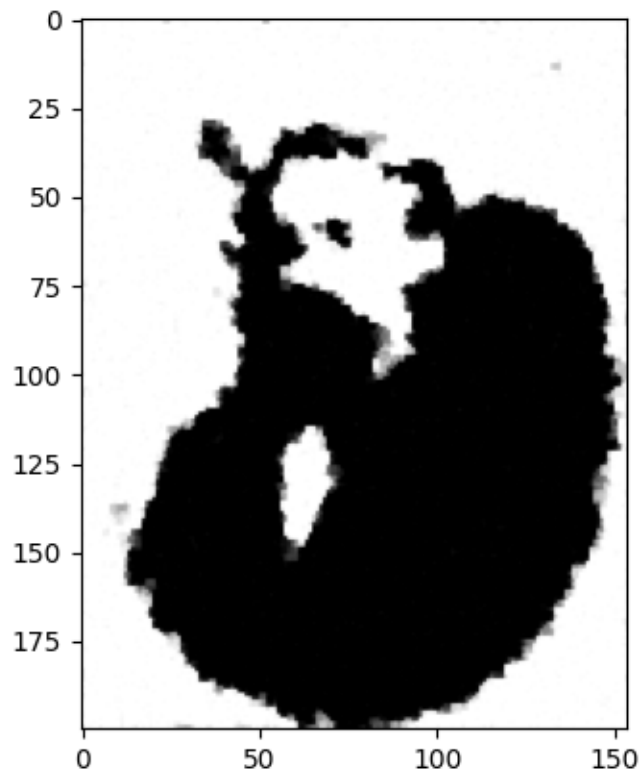
5.

6. we know that true mean value of  $y$  is  $E[y] = 0$ . When  $w$  is greater, the mean value of  $y$  takes longer to converge to 0 because the variables are positively correlated and there is a stronger dependence between them. The curves also show that the convergence rate depends on the value of  $w$ , with higher values of  $w$  leading to slower convergence.



7. mean per-pixel squared difference of from the true output :0.32157412987012984
8. Describe (a) how you tried to find better parameters (there is no single correct answer here) (b) show an image of your final denoised image and (c) report the final error
- (a) so I run the loop that  $w = [0.2, 0.4, 0.6, 0.8, 1.0]$  and  $b = [0.1, 0.5, 1, 1.5, 2.0]$  then find the best mean value from that

mse	b	w
0.8835606363636366	0.1	0.2
0.7981681818181819	0.5	0.2
1.04176861038961	1	0.2
1.2669878181818188	1.5	0.2
1.394225922077923	2	0.2
0.33841142857142864	0.1	0.4
0.37976649350649344	0.5	0.4
0.7643041168831168	1	0.4
1.2758485584415593	2	0.4
0.14346701298701292	0.1	0.6
0.1321160389610389	0.5	0.6
0.7998220519480522	1.5	0.6
1.0827960129870136	2	0.6



```
0.14589348051948053 0.1 0.8
0.1227434935064935 0.5 0.8
0.1499607662337662 1 0.8
0.4392784675324674 1.5 0.8
0.82739312987013 2 0.8
0.14602092207792208 0.1 1.0
0.12181210389610389 0.5 1.0
0.12121620779220778 1 1.0
0.18067115584415583 1.5 1.0
0.4873041558441558 2 1.0
```

so from this result, best vlaue is  $b = 1$  and  $w = 1$   $mse = 0.12121620779220778$