1 Introduction

1.1 Boltzmann Machines

A Boltzmann Machine consists of a set of binary units, s and all these units are connected to each other with a weight, w_{ij} associated with each connection. The global energy, E of the Boltzmann Machine is given by:

$$E = -\left(\sum_{i<j} w_{ij} s_i s_j + \sum_i \theta_i s_i\right)$$

While learning from data, we try to adjust the weight parameters such that the stationary distribution of the Boltzmann machine closly represents our dataset. For determining the stationary distribution of the Boltzmann Machine we start with random states for all the binary units and iterate over them setting them to $+1$ with a probability of $\frac{1}{1+e^{-2a_i}}$, -1 otherwise. After a few iterations the machine converges to its stationary distribution.

Now for comparing this stationary distribution to our dataset we generate some samples from the Boltzmann Machine and using that we compute the free expections using:

$$< s_i >= \sum_s s_i p(s), \quad < s_i s_j >= \sum_s s_i s_j p(s)$$

Similarly we compute clamped expectations from our dataset using:

$$< s_i >_c = \frac{1}{P} \sum_\mu s_i^\mu, \quad < s_i s_j >_c = \frac{1}{P} \sum_\mu s_i^\mu s_j^\mu$$

and then we update our weights based on these values:

$$\begin{aligned}
&w_{ij}(t+1) = w_{ij}(t) + \eta \frac{\partial L}{\partial w_{ij}} \\
&\theta_i(t+1) = \theta_i(t) + \eta \frac{\partial L}{\partial \theta_i} \\
&\frac{\partial L}{\partial \theta_i} =< s_i >_c - < s_i > \\
&\frac{\partial L}{\partial w_{ij}} =< s_i s_j >_c - < s_i s_j >
\end{aligned} \tag{1}$$

2 Research Questions

1. Adding noise to the MNIST Dataset
2. Sampling vs Mean Field

3 Results

3.1 Accuracy of the model with varying levels of noise

Each image in the MNIST dataset is represented by a 28x28 pixel. We first binarized it and added noise so that the matix C doesn't get singular.

For adding the noise to the image we created a noise mask for each pixel. Each pixel in the mast has a value of -1 with probability p and value 1 with probability $1-p$. Then we do an element-wise multiplication of the binary image and the noise mask. Therefore when $p = 0$, there shouldn't be any distortion in the image whereas for $p = 1$ every bit should be flipped but there won't be any change in the structure. For $p = 0.5$, the maximum noise will be obtained and the image will be completely distorted. We can see these effects in Fig. 1.

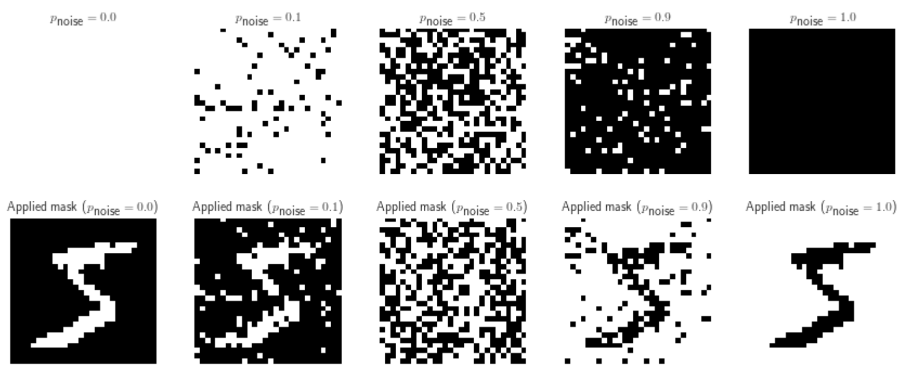

Figure 1: Different noise levels along with the final masked images

We tried to run our Boltzmann machine on varying levels of noise and computed the accuracy of our model.

There are 3 main features of the graph:

1. **Low accuracy at low noise levels**
   In Fig. 4, we can see that for very low levels of noise (around 0.00 - 0.03) we have an accuracy of around 0.1 which is equivalent to random guessing. This low accuracy can be explained by the fact that due to low noise levels some of the pixels in the all the images are the same. For example the top-left pixel or the top-right pixel will be off in almost all the images. And these constant pixels makes the matrix C approach towards singularity resulting in low accuracy.

2. **Highest accuracy at around noise level of 0.1**
   The accuracy of the model starts increasing at around $p = 0.04$, gets around 0.9 accuracy for $p \approx 0.5$ reaching the maximum at $p \approx 0.1$ and the gradually decrease as we increase the noise level in the data.

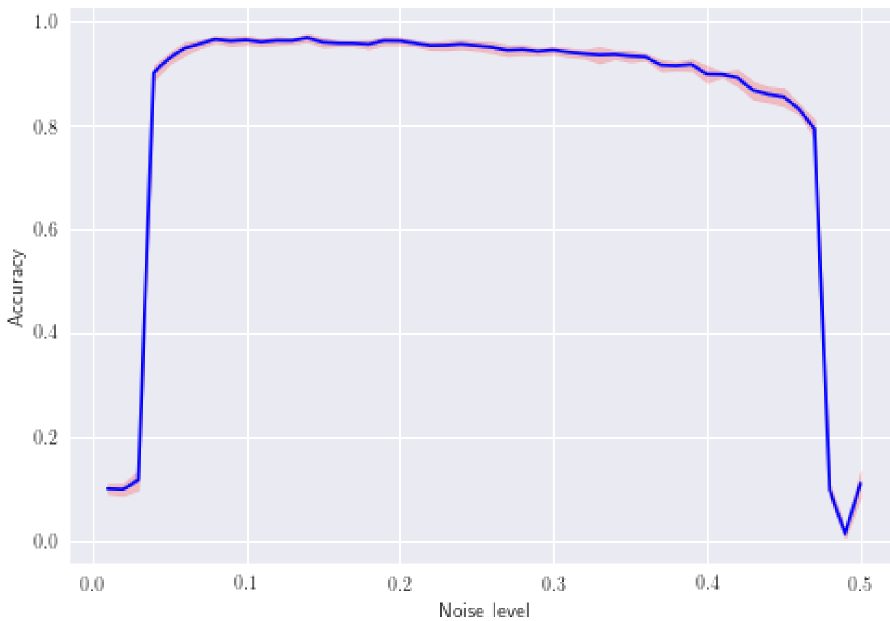

Figure 2: Accuracy of the model with varying noise level

3. **Dip at $p = 0.47$ and accuracy of 0.1 at $p = 0.5$** We see a dip in the accuracy value at $p = 0.47$ where it is almost 0. We coudn't find any good possible explanation for this behaviour. For $p = 0.5$ we again get an accuracy of 0.1. This behaviour can be explained since our images are completely distored now, the model's performace is equivalent to random guessing.

3.2 Comparision of Sampling Methods and Mean Field Approximation

For learning a Boltzmann machine we need to compare the free and the clamped statistics. The probability distribution represented by a Boltzmann machine is given by:

$$p(s) = \frac{1}{Z} e^{-E(s)}$$

where:

$$\begin{aligned} E(s) &= -\frac{1}{2} \sum_{ij} w_{ij} s_i s_j + \sum_i \theta_i s_i \\ Z &= \sum exp(-E(s)) \end{aligned} \tag{2}$$

Here if we try to compute the distribution using any exact method we will need to compute the value of Z for which we will need to compute the sum over all the possible 2^n states of the Boltzmann machine. This is not feasible even in the case of relatively smaller networks because we need to compute the free statistics in each iteration until convergence. Therefore we need to use some approximate techniques. For the assignment we used Gibbs sampling and Mean Field theory for approximating the free statistics.

1. **Behaviour in case of Gibbs Sampling** We tested the effect of varying the number of samples and burn in period on the convergence of our learning rule. For this we used a network of 10 neurons and trained on 50 random input patterns. We initialized the weights and biases using random samples from a Normal Distribution with mean 0 and variance 1.

   For comparing the rate of convergence, we fitted a straight line to the absolute change in weights with number of iterations as shown in Fig. **??**. We also plotted a grid (Fig. **??**) for value of slope for different values of burn-in samples and number of used samples.

2. **Approximating using Mean Field Theory** TODO: Mean Field theory

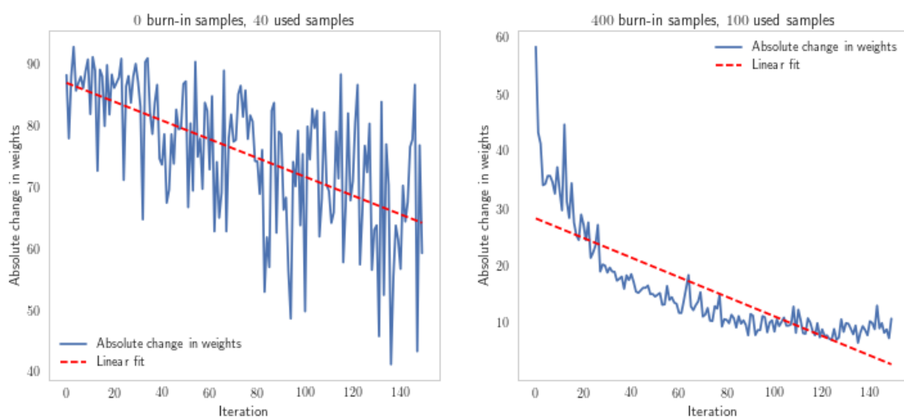

Figure 3: Absolute change in weight with iteration

4 Conclusion

5 Appendix

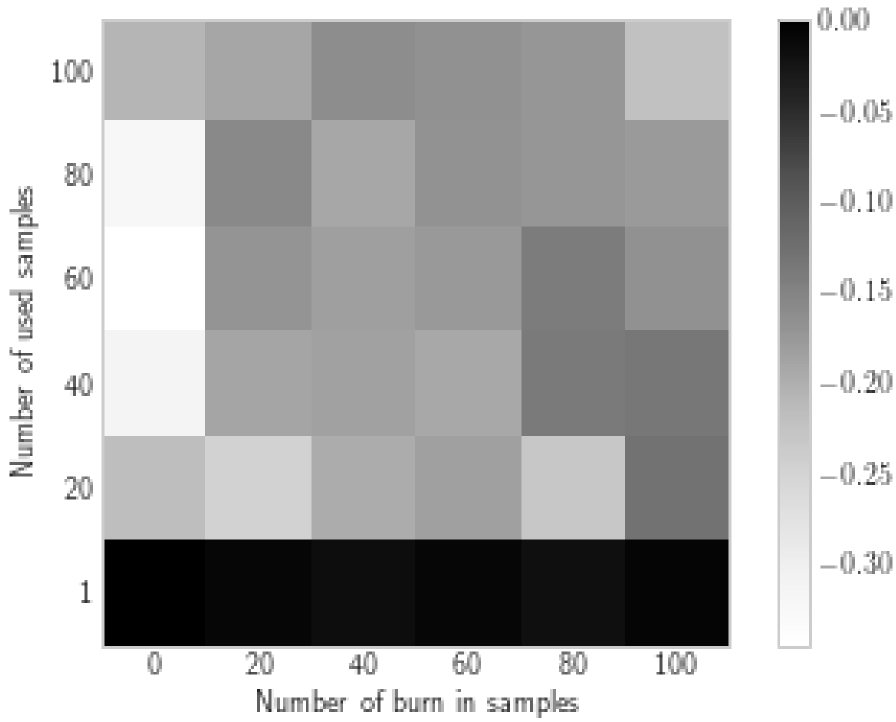

Figure 4: Variation of slope for different values of used samples and burn in samples